Training Near Equilibrium: Why Stable Learning Rates, Slow Refinement, and "Defect Rejection" Make Large Language Models Take So Long

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Large language models are often described as "just" big neural networks trained with gradient descent, yet practitioners know a harder truth: you cannot simply turn the learning rate up and finish quickly. Training must stay within a narrow regime where progress is steady but not explosive, because overly aggressive updates lock in brittle shortcuts, amplify noise, and can destabilize optimization entirely. This paper proposes a physical analogy to explain that regime: high-quality crystals typically grow best when conditions are only slightly favorable to growth over dissolution, allowing mistaken attachments to detach before being trapped. In LLM training, an analogous balance appears between forces that commit structure (parameter updates that fit patterns in data) and forces that erase or resist premature commitment (stochasticity, weight decay, data augmentation, averaging, and schedule "cooling"). The result is not merely slower training; it is training that remains self-correcting long enough to produce coherent generalization rather than brittle memorization. We develop this "near-equilibrium training" frame, show where it matches practice and where it fails, and translate it into actionable design choices: learning-rate schedules, optimizer regimes, regularization pressure, data curation, and post-training alignment constraints. The goal is not poetry, but an operational intuition for why reliable capability emerges slowly.

Keywords: large language models, LLM training, learning rate schedule, edge of stability, stochastic gradient descent, generalization, sharp minima, weight decay, exponential moving average, annealing, optimization stability, scaling laws, curriculum learning, regularization, diffusion of errors.

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1. The Puzzle: Why LLMs Take So Long to Train

At first glance, the recipe for a large language model looks almost embarrassingly simple: take a neural network, feed it vast amounts of text, and adjust its parameters to reduce prediction error. From that perspective, it is natural to ask why training takes weeks or months on enormous clusters. If a model is "learning," why not simply push harder until it learns faster?

The answer is that LLM training is constrained by two different kinds of scale that do not trade off linearly: the scale of the computation itself and the scale of the optimization dynamics. Compute scale is the obvious one: the number of parameters, tokens, layers, and forward–backward passes. But optimization scale is the less intuitive one: the training process has stability limits, self-correction requirements, and late-stage refinement dynamics that impose a kind of "speed limit" even if you had infinite hardware. When training runs beyond that limit, the model does not merely learn faster; it often learns worse, becomes unstable, or collapses into brittle solutions that look impressive on some metrics but fail under distribution shift.

There is also a third, quietly decisive factor: LLMs are not learning a narrow task with a tidy objective. They are compressing a sprawling, heterogeneous distribution of human language into a finite set of weights. The training signal is locally simple (predict the next token), but the global target is immense: syntax, semantics, domain knowledge, social registers, coding patterns, reasoning templates, and long-range dependencies. Progress is therefore inherently incremental, because a huge portion of what matters is "rare but important." Many of the behaviors that users care about live in the tail of the data distribution, and tails are expensive: you either train longer or accept that those behaviors will remain unreliable.

In short, training takes a long time not because the field has failed to "optimize training," but because reliable capability is a product of stable learning dynamics applied repeatedly at scale. The slowness is not purely waste. Much of it is structural.

1.1 Compute Scale Versus Optimization Scale

Compute scale is the part everyone sees. If you increase parameters, you increase the cost per training step. If you increase tokens, you increase the number of steps needed to cover the data (or to reach the same number of effective passes). If you increase context length, you increase the cost of attention and memory. In this sense, training time is simply arithmetic: more model and more data means more floating-point operations.

But optimization scale is a different animal. Even with unlimited hardware, you cannot usually collapse training into a tiny number of giant steps, because the optimization landscape and the stability conditions do not allow it. Deep networks trained with stochastic gradient descent and its variants exhibit regimes where training is smooth and productive, and regimes where it becomes chaotic or brittle. These regimes are not a matter of taste; they are a consequence of

curvature, noise, and the way high-dimensional parameter updates interact with the data distribution.

A useful way to see the difference is to separate the questions:

1. How much compute is required to evaluate the model and its gradients?
2. How many update steps are required for those gradients to accumulate into coherent generalization?

The first question is engineering and scaling. The second is dynamics and learning theory. You can reduce the first with better hardware utilization, better kernels, better parallelism, and more efficient architectures. You can sometimes reduce the second with better objectives, better data, better schedules, or better initialization. But you cannot reduce it arbitrarily without paying a price, because the second question is tied to how the model "settles" into stable structure.

This is why LLM training often looks like a two-phase project. Early training can tolerate larger, more energetic updates because the model is mostly learning broad statistical regularities. Later training becomes much more sensitive: changes that once improved everything now risk damaging hard-won structure, overfitting tails, or producing regressions in behavior. The late phase is not "wasted time." It is the refinement period in which the model becomes less jagged: fewer instabilities, fewer spurious tricks, more reliable generalization.

So compute scale tells you why training is expensive. Optimization scale tells you why training is time-consuming even when you spend that compute efficiently.

1.2 The Myth of "Just Increase the Learning Rate"

From the outside, it seems plausible: if each step updates the model, larger steps should get you to the destination faster. But the learning rate is not a throttle on speed alone. It is also a knob that controls stability and the quality of the solution you converge to.

When the learning rate is too high, training can fail in several ways:

- The loss can become unstable, oscillating or exploding rather than decreasing smoothly.
- The model can "thrash," repeatedly overwriting representations before they consolidate.
- The optimizer can settle into brittle parameter configurations that fit the training signal but generalize poorly.
- You can induce catastrophic events: sudden divergence, numerical issues, or irreversible degradation in downstream metrics.

Even below outright divergence, overly aggressive learning can cause a more subtle failure: it can entrench defects. In the crystal analogy, this is like growing so quickly that misattachments and impurities get buried rather than rejected. In training, "defects" include shortcut features, dataset quirks, and unstable internal representations that work in-sample but fail out-of-sample. Large updates can force the network into sharp, high-curvature regions that look good on immediate loss reduction but are fragile to perturbations.

This is why practitioners talk about training near an "edge of stability." There is often a narrow band where learning is both fast and stable. Pushing above it doesn't give you proportionally faster learning; it gives you qualitatively different dynamics. And these dynamics are not merely worse in a gradual way. They can be worse abruptly, because stability in high-dimensional systems often breaks suddenly.

The myth persists because short demonstrations sometimes seem to support it. On small models or short runs, higher learning rates can look like free speed. But the failure modes frequently reveal themselves only with scale: longer training, larger models, more diverse data, and more stringent evaluations. When you care about robust performance across many tasks and domains, the costs of instability accumulate, and "fast" becomes "fragile."

So LLM training does not proceed slowly because we refuse to turn the knob. It proceeds slowly because the knob is attached to the structural integrity of learning itself.

1.3 A Preview of the Near-Equilibrium Thesis

The near-equilibrium thesis is an attempt to give a single operational intuition for the puzzle. In crystal growth, high-quality crystals tend to form when the solution is only slightly supersaturated: growth is favored, but not by much. The system remains close enough to equilibrium that mistaken attachments can detach before they are trapped, and that impurities are less likely to be incorporated. Quality comes from a balance between a driving force that builds structure and a corrective force that rejects errors.

Translate that to LLM training. Parameter updates "grow" structure: they commit the model to patterns in the data. But training also needs "correction forces" that prevent premature commitment and allow the model to revise. These include stochasticity (which helps avoid brittle traps), regularization (which penalizes overly complex or overly confident fits), smoothing and averaging (which damp high-frequency parameter noise), and schedule cooling (which gradually shifts from exploration to refinement). The claim is not that LLMs literally equilibrate in a thermodynamic sense. The claim is that good training behaves like a process that stays just close enough to a self-correcting regime that defects are rejected rather than fossilized.

This frame immediately explains two otherwise confusing realities:

- Training can be compute-hungry and still require many steps, because the objective is not merely to reduce loss quickly but to do so in a way that preserves self-correction as long as possible.
- The later stages of training are slow by design, because refinement requires smaller, less disruptive updates that consolidate structure instead of constantly rearranging it.

The near-equilibrium thesis also makes a prediction: if you try to make training dramatically faster without adding new correction forces, you should expect more defects. Those defects may not appear in headline metrics, but they will surface as brittleness, inconsistency, poor out-of-distribution behavior, or alignment instability. Conversely, real speedups often come not from "pushing harder," but from improving the system's ability to self-correct while moving: better data, better objectives, better optimizers, better schedules, and better evaluation signals that detect defects early.

The rest of the paper builds this idea carefully: first by making the crystal analogy precise enough to be useful, then by mapping training mechanisms onto the growth-versus-correction picture, and finally by extracting design heuristics and failure diagnostics that turn the intuition into practice.

2. Crystal Growth as a Model of Quality Under Gentle Driving

Crystals are a convenient physical metaphor because they make "quality" visible. A well-grown crystal has smooth facets, internal clarity, and a lattice with relatively few defects. A poorly grown crystal often looks cloudy, fractured, striated, or dendritic, and its internal structure contains dislocations, inclusions, and strain. The striking part is that these outcomes are not mysterious: they are strongly shaped by how hard you "push" the system away from equilibrium.

Crystallization from solution is governed by competing surface processes. Building the crystal requires that solute units arrive at the crystal surface and attach in a way that matches the lattice. Dissolution is the reverse: surface units detach and return to solution. At equilibrium, attachment and detachment balance. In growth, the balance is tipped: the environment is adjusted so attachment is favored. But the magnitude of that tipping matters. Too small, and nothing grows. Too large, and the system grows quickly but sloppily, often producing many small crystals and embedding defects that cannot be repaired.

This is the physical foundation for the near-equilibrium intuition. The highest-quality crystals are often produced not by maximizing growth rate, but by maintaining a gentle, stable driving force that keeps the surface dynamics reversible enough to correct mistakes before they are trapped.

2.1 Supersaturation, Growth Rate, and Defect Formation

In solution growth, the central control parameter is supersaturation: the extent to which the solute concentration exceeds its equilibrium solubility at the given temperature and solvent conditions. Supersaturation provides the thermodynamic "push" for crystallization. It sets the chemical potential difference between solute in solution and solute in the crystal.

As supersaturation increases, two things typically happen:

First, growth accelerates. More solute is available, and attachment becomes more favorable. This can be desirable up to a point.

Second, nucleation becomes easier. Instead of growing one seed crystal, the solution may spontaneously form many nuclei. That yields a shower of small crystals or polycrystalline aggregates rather than a single well-formed crystal. Even if you obtain a larger specimen, it may be a cluster of misaligned domains.

Defects rise with aggressive driving for several reasons:

- **Kinetic trapping at the surface.** At high supersaturation, attachment is frequent and rapid. Surface units may not have time to diffuse along the surface to find a low-energy, correct lattice site. Misplaced units are more likely to be buried by subsequent growth before they detach.
- **Rough growth instead of layer-by-layer growth.** Under gentle conditions, crystals often grow by step-flow: layers propagate across faces via terraces and steps. Under stronger driving, growth can become "rough" with many simultaneous attachment sites, producing irregular morphology and more defects.
- **Dendritic and branching morphologies.** Strong driving can create instabilities where protrusions grow faster than flat faces because they capture solute more effectively. This produces dendrites and branching structures. These can be beautiful but typically reflect nonuniform growth and internal disorder.
- **Stress and strain accumulation.** Fast growth can lock in strain due to thermal gradients, concentration gradients, or anisotropic growth rates, leading to dislocations or microcracks.

A key point is that "defect formation" is often not about a single mistake; it is about the inability of the system to correct mistakes while continuing to grow. Aggressive supersaturation makes

growth effectively irreversible at the microscopic timescale: once a unit attaches, it is quickly buried.

This is the first bridge to LLM training. Large learning rates and strong optimization “push” can likewise turn learning into a process that commits patterns quickly but loses the ability to revise them cleanly.

2.2 Error Rejection Near Equilibrium

Near equilibrium, attachment and detachment both occur frequently. Net growth may still be positive, but only slightly. That is the regime where “error rejection” becomes effective.

Why? Because reversibility is a quality control mechanism.

When a solute unit attaches incorrectly, the local bonding is weaker or geometrically strained compared to a correct attachment. In a near-equilibrium regime, that weak attachment has a meaningful chance to detach before it becomes stabilized by neighboring attachments. The surface can explore configurations and settle preferentially into lower-energy lattice-consistent arrangements. The crystal face remains smooth because steps and terraces propagate in an orderly way, with fewer random protrusions.

This is not magic; it is a competition of rates:

- The rate of correct attachment at stable sites
- The rate of incorrect attachment at unstable sites
- The rate of detachment of unstable attachments
- The rate at which subsequent growth buries whatever is present on the surface

If the system is driven too hard, “burying” wins. If the system is driven gently, “detaching wrong fits” wins often enough to keep defect density low.

Another benefit of near-equilibrium growth is selectivity. If an impurity species can attach but does not match the lattice well, gentle conditions increase the probability that it will be rejected. Strong conditions increase impurity incorporation because the crystal is growing so quickly that it captures whatever is available.

This also clarifies why “slow growth” is sometimes not merely slower but qualitatively different. The system is not simply doing the same thing at a lower rate; it is operating in a regime where local corrections occur at the surface and the crystal’s morphology remains stable.

In AI terms, the near-equilibrium regime corresponds to training dynamics that preserve a kind of reversibility: the model continues to revise representations rather than hardening them prematurely, and mechanisms exist that damp spurious updates before they dominate.

2.3 When Slow Growth Fails: Impurities, Gradients, and Instability

The crystal metaphor is useful precisely because it has failure modes. “Slow” is not automatically “good.” Quality depends on what limits correction and what creates defects.

Several common reasons slow growth can still fail:

- **Impurities and selective adsorption.** Some impurities bind strongly to certain crystal faces or step edges. Even at low supersaturation, they can poison growth, distort morphology, or become incorporated as inclusions. In some systems, slower growth can even increase exposure time to impurities, increasing incorporation in specific ways.
- **Concentration gradients and depletion layers.** A growing crystal consumes solute near its surface, creating a boundary layer. If mixing is insufficient, local concentration drops near the surface while remaining higher in bulk, producing nonuniform growth conditions. This can cause striations or uneven face development. Gentle driving does not eliminate gradients; it can make them more pronounced if transport is limiting.
- **Temperature gradients.** Solubility depends on temperature. Even small thermal gradients can create local supersaturation or undersaturation zones, leading to alternating growth and etching, internal stress, or sector zoning. A “slow” process in a thermally unstable environment can produce repeated micro-instabilities that degrade quality.
- **Convection and hydrodynamic noise.** Flow patterns can deliver solute unevenly and cause fluctuations in effective supersaturation at the surface. The crystal may experience a jittering environment even if the bulk solution is controlled.
- **Ostwald ripening and competing crystals.** Over long times, smaller crystals can dissolve and larger crystals grow, which can be beneficial if controlled but can also lead to pitting or instability if conditions drift near undersaturation. If the system slips below equilibrium at the surface, dissolution can create etch pits and dislocations.

These failure modes matter for the analogy because they show that the “near-equilibrium” thesis needs two ingredients: gentle driving and stable control. Gentle driving without control can produce a system that is perpetually on the verge of switching between growth and dissolution in a noisy way. That yields defects too, just via a different pathway.

Translate this to LLM training. Small learning rates and careful schedules do not guarantee quality if the data is contaminated, the objective induces misalignment, or the training environment introduces uncontrolled shifts. Slowness can simply mean you are slowly accumulating the wrong structure.

So the crystal metaphor encourages a stronger claim: quality requires both a self-correcting regime and a training environment that does not inject persistent, structured "impurity" signals.

2.4 What the Analogy Is and Is Not Claiming

This analogy is a tool for intuition, not a literal identity. It is important to be explicit about where it holds and where it breaks.

What it is claiming:

- **There is a tradeoff between speed and defect rejection.** Pushing the system harder can accelerate net progress while increasing the probability that mistakes become embedded.
- **Near-equilibrium regimes support self-correction.** When reverse moves remain plausible, wrong commitments can be undone before they harden.
- **Control stability matters as much as gentleness.** A gently driven process with fluctuating conditions can still produce defects.
- **Quality often emerges late through refinement.** A long, slow phase can function as a polishing step that reduces defect density and improves coherence.

What it is not claiming:

- **LLMs do not literally equilibrate thermodynamically.** Training is not a physical lattice assembling from a solution, and gradients are not chemical potentials in a strict sense.
- **There is no simple one-to-one mapping from supersaturation to learning rate.** "Driving force" in training is a composite of learning rate, batch size, optimizer dynamics, gradient noise, normalization, and data properties.
- **Defects in models are not microscopic lattice errors.** They are functional and representational artifacts: brittle generalization, shortcut reliance, or pathological behaviors. The analogy concerns the mechanism of how errors become entrenched, not their physical form.
- **Slow training does not guarantee virtue.** Just as slow crystal growth can fail under impurities or gradients, slow training can fail under bad data, mispecified objectives, or insufficient evaluation of defects.

The purpose of the analogy is pragmatic: to provide a unified mental model for why "more aggressive" training often backfires and why late-stage refinement is not optional if you want reliability. It also sets up the next move in the paper: to identify what in training plays the role of

reversibility and defect rejection, and what kinds of “impurities” and “gradients” correspond to data contamination, distribution shift, and objective mismatch.

In other words, the analogy is meant to discipline our intuitions. It suggests that the central question is not “How do we make training faster?” but “How do we move faster while preserving self-correction, and how do we detect when we are embedding defects?”

3. The Training Map: What Corresponds to Growth and Dissolution in SGD

If the crystal metaphor is to be more than a poetic flourish, it needs a concrete mapping: what, in stochastic gradient descent and modern deep-learning practice, plays the role of “growth” and what plays the role of “dissolution”? The goal is not to force a one-to-one equivalence, but to identify a family of mechanisms that either (a) commit structure or (b) prevent premature commitment and allow revision.

In crystals, growth is the net accumulation of correctly placed units into a coherent lattice. Dissolution is the ability of surface units to detach, which—near equilibrium—functions as a quality control channel. In neural network training, the closest analogue to growth is the accumulation of parameter changes that stabilize useful representations. The closest analogue to dissolution is any mechanism that keeps updates from hardening too quickly, that discourages brittle solutions, and that allows the system to “back out” of bad commitments before they become entrenched.

The trick is to see training not as a single force (minimize loss), but as a balance of forces: some push the model to fit the training signal; others constrain, smooth, or destabilize fragile fits so that only robust structure remains. When that balance is tuned well, training behaves like a gently driven process that builds coherence while continuously rejecting defects.

3.1 Parameter Updates as “Lattice Growth”

In the crystal story, growth is physical accretion: units attach and become part of the crystal. In training, “accretion” is the accumulation of weight updates. But what makes the analogy nontrivial is that the updates don’t merely store facts; they create a distributed internal geometry—representations and circuits—that organizes how the model responds to inputs.

A single gradient step does two things at once:

- It reduces error on the current minibatch by adjusting parameters in the direction that locally decreases loss.
- It also changes the internal representation landscape, which will shape how future data is processed and learned.

This matters because “good structure” in an LLM is not simply a set of memorized examples. It is a collection of stable representational motifs: token embeddings that capture semantic neighborhoods, attention patterns that track syntactic dependencies, feed-forward transformations that act like feature extractors, and higher-layer circuits that integrate long-range context. As training proceeds, these motifs become increasingly stable. That stability is the training analogue of lattice coherence.

The growth analogy is strongest when you focus on three properties of parameter updates:

- **Irreversibility in practice.** Even though, in principle, later updates can undo earlier ones, in large-scale training many changes become effectively irreversible because the system continues moving while building on what has already formed. Certain representational commitments become the substrate for later learning.
- **Local compatibility constraints.** In a lattice, a new unit must fit the local geometry. In training, a new update must remain compatible with existing representations or it will disrupt them. Late in training, when representations are more structured, large incompatible updates can cause regressions.
- **Defect burial.** If early updates create a shortcut feature that improves loss quickly, later updates may build on it. That shortcut becomes “buried” inside the model’s behavior: not because it is physically trapped, but because it becomes entangled with downstream computations. Removing it later can be difficult without harming other learned functions.

Seen this way, the learning rate and effective step size are not just speed controls. They determine how quickly and how irreversibly structure is committed. When step sizes are large, training can commit brittle structure that is difficult to revise. When step sizes are moderate and stable, training has time to consolidate robust structure and to revise unstable commitments.

This sets up the need for a “dissolution-like” channel: something that keeps training flexible enough to reject fragile structure.

3.2 Gradient Noise and Stochasticity as Reversible Dynamics

In solution growth, dissolution provides reversibility: attachments can be undone before they harden. In SGD, the closest cousin is stochasticity—especially gradient noise arising from minibatch sampling, but also other noise sources introduced intentionally or incidentally.

Why does noise help? Because deterministic optimization can over-commit to narrow solutions. In high-dimensional, nonconvex landscapes, there are many minima and many flat regions, and not all are equally robust. Stochasticity helps in several related ways:

- **It prevents premature locking into sharp basins.** Sharp minima are regions where small parameter changes produce large loss changes. They can fit training data well but often generalize worse or behave more brittlely under distribution shift. Gradient noise acts like a shaking of the system that makes it harder to settle into narrow crevices.
- **It creates a form of implicit regularization.** Even without explicit penalties, SGD's noise can bias training toward flatter regions of parameter space, because those regions are more stable under perturbations.
- **It enables continual revision.** If updates were perfectly consistent and large, the model might harden early representations too quickly. Noise keeps the system slightly "fluid," letting it reconfigure as new data arrives.

This is where the analogy to near-equilibrium crystallization becomes intuitive. Near equilibrium, attachments and detachments both occur frequently. In SGD, stochasticity means that an update is not a final verdict. Each step is one vote among many, and the noise ensures that a fragile pattern that only "works" for a narrow set of batches is less likely to become a stable attractor.

However, as in crystals, stochasticity has a "too much" regime. Excessive noise can prevent consolidation: the model keeps rearranging and never crystallizes. In practice, this appears as poor convergence, underfitting, or unstable metrics. The sweet spot is a controlled level of noise that allows exploration and defect rejection early, and reduced noise or smaller steps later so that stable structure can be polished and retained.

This also helps explain why batch size matters. Large batches reduce gradient noise, making training more deterministic; small batches increase noise. Many empirical results in deep learning can be reframed as tuning the "reversibility" channel through batch size, learning rate, and schedules.

3.3 Regularization as a Continuous "Etching" Pressure

In crystals, dissolution near equilibrium can be seen as a kind of gentle etching: unstable attachments are removed. In training, explicit regularization plays a similar role by continuously applying pressure against certain kinds of commitments.

Regularization is often described as a way to prevent overfitting. But in the near-equilibrium frame, it is more specific: it counteracts the tendency of optimization to lock in brittle structure. It is a standing force that continuously discourages "defects," where defects in this context are overly complex, overly confident, or overly norm-inflated representations that fit the training signal but lack robustness.

Different forms of regularization play different roles:

- **Weight decay (L2 regularization).** This penalizes large weights and encourages smaller norms. Interpreted structurally, it discourages highly amplified, high-curvature solutions. It is a continuous pressure toward simpler, more stable parameter configurations.
- **Dropout and related stochastic regularizers.** These introduce noise into activations during training, preventing the model from relying too heavily on any single pathway. This encourages redundancy and robustness—akin to forcing growth to proceed through stable patterns rather than fragile single points.
- **Label smoothing.** This reduces the incentive to become maximally confident on training examples. It can blunt the formation of razor-sharp decision surfaces and reduce susceptibility to overconfident misgeneralization.
- **Constraint-like techniques.** Gradient clipping, norm constraints, and other boundedness mechanisms prevent rare but extreme gradient events from imprinting large, destabilizing changes.

All of these resemble etching in the following sense: they do not merely slow training. They selectively penalize particular kinds of structure. In crystals, dissolution is not uniform; unstable attachments are preferentially removed. In training, regularization preferentially suppresses high-norm, high-confidence, overly brittle solutions.

But again, the analogy must respect failure modes. Etching can be too strong. Over-regularization can wash away useful structure and produce underfit, bland models. The goal is not maximal dissolution; it is just enough correction pressure that defects do not accumulate faster than the system can reject them.

This balance also explains why different tasks and datasets require different regularization strengths. Some datasets are “dirty” in the sense that they contain spurious correlations. Others are clean and require less corrective pressure. In the crystal metaphor, the “chemistry of the solution” determines how much etching is needed to prevent impurity incorporation.

3.4 Model Averaging as Smoothing and Defect Annealing

Crystals can be improved not only by slow growth but also by annealing: allowing internal strain and defects to relax over time. Training has a close analogue: model averaging methods that smooth out high-frequency parameter noise and yield more stable solutions.

There are several forms of averaging, but they share a core idea: rather than trusting the instantaneous parameter state, you integrate over a trajectory.

- **Exponential Moving Average (EMA).** EMA maintains a smoothed version of model weights by averaging across training steps with an exponential decay. This tends to produce a model that generalizes better and behaves more stably, because it reduces the impact of transient fluctuations.
- **Stochastic Weight Averaging (SWA) and related methods.** These average weights across multiple points in training, often near the end, producing a solution that lies in a flatter region of the loss landscape.
- **Checkpoint ensembling.** Even without formal averaging, combining predictions from multiple checkpoints often improves robustness, reflecting the fact that any single point is a noisy sample of a broader region.

In the near-equilibrium frame, averaging is a defect-reduction mechanism. It functions like this:

- SGD introduces noise and exploration. That noise is useful early, but it also means the final parameters contain high-frequency components that are not essential to generalization.
- Averaging filters those components, leaving behind the stable structure that persists across time.

This is similar to annealing in materials: thermal motion allows rearrangements that reduce strain and eliminate certain defects. Averaging allows the model to "settle" into a smoother, flatter configuration that is less sensitive to perturbations.

A crucial subtlety is that averaging works best when the training trajectory is already in a good region. If training is unstable or drifting, averaging can smear together incompatible states. So averaging is not a replacement for stable training; it is a refinement that assumes stability.

Put together, these four elements—updates as growth, stochasticity as reversibility, regularization as etching, and averaging as annealing—create a coherent training map. They also clarify why "faster training" is hard. To speed up growth (larger steps, fewer steps) without increasing defects, you must strengthen or redesign the correction mechanisms: better data, better objectives, better regularization schedules, improved noise calibration, and better averaging or stabilization. Otherwise, you get rapid accretion of structure that looks like learning, but behaves like a defect-rich crystal: impressive at a glance, unreliable under stress.

The next sections build from this map to a central practical claim: there is a narrow operating band—an edge-of-stability regime—where these forces balance in a way that is both fast and self-correcting. Understanding that band is key to understanding why LLM training takes as long as it does and why reliable models are expensive.

4. The Edge of Stability: The Narrow Band Where Learning Works Best

In practice, training a large language model is rarely limited by the ability to run the computation. It is limited by the ability to run it stably while continuing to improve. Practitioners learn this quickly: there is a regime where training "just works," a regime where it is painfully slow, and a regime where it becomes unstable or silently degrades. The surprising part is how narrow the good regime can be—especially at scale.

This motivates the concept of an edge of stability: a band of hyperparameter settings (especially effective step size) that is close to the maximum stable regime but not beyond it. In that band, training makes fast progress while remaining self-correcting. Outside it, you either squander compute (too conservative) or you pay for "growth with defects" (too aggressive) or outright collapse.

In the crystal analogy, this is the zone of slight supersaturation with stable control: enough driving force to grow, but not so much that the surface becomes rough and defect-prone. In SGD, it is the zone where updates are energetic enough to traverse the landscape efficiently while still allowing the correction mechanisms—noise, regularization, averaging, and schedule cooling—to keep the model from hardening into brittle structure.

4.1 Stability Limits and Why Divergence Is Abrupt

People often imagine instability as a gradual phenomenon: you increase the learning rate a bit, the model trains a bit worse, you increase it again, it trains worse still. But large-scale deep learning often behaves differently. Training can appear healthy right up to a point, and then fail suddenly.

This abruptness comes from the nature of stability in iterative dynamical systems. A training step is a transformation of parameters. When step sizes are small enough, the transformation moves the parameters downhill in loss reliably. When step sizes are too large relative to the local curvature of the loss landscape, the update can overshoot. Overshooting does not merely slow progress; it can flip the update from corrective to destructive, amplifying error rather than reducing it.

Several concrete phenomena contribute to the "cliff edge":

- **Curvature spikes.** The loss landscape is not uniformly curved. Some directions in parameter space have much higher curvature than others. As training proceeds, the model may wander into regions where curvature increases. A learning rate that was safe yesterday becomes unsafe today.
- **Feedback loops in representations.** In deep networks, layers feed into layers. An unstable change in early representations can destabilize gradients elsewhere, producing cascading effects. What looks like a small instability becomes an avalanche.

- **Rare batches and tail events.** Even if average gradients are well-behaved, occasionally a batch has unusual statistics or contains hard examples that generate larger gradients. If the system is near the stability limit, these rare spikes can push it over.
- **Numerical and scaling sensitivities.** Modern training uses mixed precision, large batch parallelism, and complex optimizer states. Near the stability edge, small numerical differences can matter. Instability can therefore appear "stochastic": one run survives, another run collapses under the same settings.

This abruptness is the training analogue of morphological instability in crystallization. A crystal can grow smoothly until a threshold is crossed, after which branching and rough growth appear suddenly. The system has moved from a stable regime to an unstable one. In LLM training, "rough growth" is often visible as loss spikes, exploding gradient norms, divergence of optimizer moments, or sudden regressions in evaluation metrics.

The key operational point is that stability is not a comfort zone; it is a boundary condition. As you approach it, your margin for disturbance shrinks. Training becomes sensitive to the very things you cannot fully control: data heterogeneity, rare batch composition, and high-dimensional curvature.

4.2 Why the Best Solutions Often Require Near-Maximal Stable Step Sizes

It would seem natural that if instability is dangerous, the best practice is to stay far away from it. Yet many experienced trainers do the opposite: they aim for learning rates and effective step sizes that are near the maximum stable level, then manage risk through schedules, warmup, clipping, and careful monitoring.

Why would that be true?

One reason is simply efficiency. If you train too conservatively, you may need far more steps to reach similar loss. That is not just a cost issue; it changes what you can afford to do. A training run that requires twice as many steps may require compromise in model size, data coverage, or experimentation, which can reduce final capability.

But there is also a quality reason that aligns with the crystal analogy. Near-maximal stable step sizes can help avoid a different failure mode: premature crystallization into a narrow basin. If steps are too small too early, the model may settle into a locally convenient configuration that fits early-learned patterns but is not the best foundation for broad generalization. In other words, overly gentle early growth can yield a crystal that "sets" too soon, leaving internal strain or suboptimal structure that is hard to reconfigure later.

In training terms, larger steps and healthy stochasticity early can:

- Encourage exploration of parameter regions that support broader generalization.

- Prevent over-commitment to early shortcuts that reduce loss quickly but generalize poorly.
- Accelerate representation formation, allowing the model to build richer internal features earlier in training.

This creates a subtle tradeoff. If you go too high, you get instability and defect burial. If you go too low, you get slow progress and sometimes early hardening into suboptimal structure.

This is why the best training recipes often have a characteristic shape:

- **Warmup:** begin with small steps while optimizer states and activations stabilize.
- **High-energy plateau:** operate near the stability edge for a substantial portion of training.
- **Cooling:** reduce step sizes late so that refinement can occur without disrupting matured representations.

That pattern mirrors seeded crystal growth: establish stable initial conditions, grow under controlled driving, then polish under gentler conditions.

4.3 Sharp Versus Flat Minima as Defect-Rich Versus Defect-Poor Structure

The sharp-versus-flat minima story has become a common way to talk about generalization in deep learning. It is not a perfect theory, but it is a powerful intuition and fits naturally into the defect metaphor.

A sharp minimum is a region of parameter space where small changes in parameters cause large increases in loss. A flat minimum is a region where parameters can move a bit without much change in loss. Flatness is often associated with robustness: if small perturbations do not hurt, the model is less sensitive to noise, distribution shift, and sampling quirks.

In the crystal analogy:

- Sharp minima resemble defect-rich crystals under stress. They are “finely tuned” in a way that makes them fragile.
- Flat minima resemble defect-poor, relaxed crystals. They tolerate small perturbations without fracture.

Why might sharpness correspond to “defects”? Because sharp solutions often reflect reliance on brittle features: narrow decision surfaces, highly amplified internal activations, or tightly coupled circuits that work only in a restricted regime. Those are the functional equivalents of internal strain or inclusions. The structure works, but it is rigid and sensitive.

The training map from Section 3 explains how training dynamics influence sharpness:

- Excessively aggressive updates can throw the model into sharp, high-curvature regions where loss can be reduced quickly but at the expense of robustness.
- Stochasticity, regularization, and averaging tend to bias toward flatter regions by penalizing or smoothing away high-curvature, high-norm solutions.

This is also a useful way to understand why “fast training” can produce brittle models even when it converges. If a run uses too-high effective step size without adequate correction mechanisms, it may still reach low training loss, but it may do so by carving sharp grooves in parameter space. The model looks good on surface metrics but fails in edge cases, long-tail reasoning, or out-of-distribution prompts.

In other words: fast growth can produce a crystal that is large but internally flawed. Similarly, aggressive optimization can produce a model that is capable in the median case but unreliable under stress.

4.4 Practical Signs You Are Above, Below, or Inside the Band

The edge-of-stability concept is only useful if it can guide practice. The following are practical signs that your training regime is likely above, below, or inside the good band. These are not universal laws, but they capture common empirical patterns.

Signs you are above the band (too aggressive, unstable, defect-prone):

- Training loss shows repeated spikes, oscillations, or sudden jumps rather than smooth descent.
- Gradient norms or optimizer moment statistics show bursts that do not recover quickly.
- Validation loss or downstream evaluations become noisy, regress, or improve in bursts followed by collapses.
- You observe “catastrophic events”: divergence, NaNs, overflow/underflow issues, or irrecoverable metric degradation.
- The model becomes behaviorally erratic: sudden changes in generation style, instability in instruction following, or increased inconsistency across prompts at similar loss.

This corresponds to a crystal regime where growth becomes rough: branching, striations, inclusions, and fractures appear.

Signs you are below the band (too conservative, stable but inefficient):

- Training loss decreases smoothly but painfully slowly; improvements per unit compute are poor.
- The model's capability metrics improve early but then plateau prematurely.
- Representational capacity seems underused: the model fails to acquire certain behaviors even with extensive training, suggesting it is not traversing the landscape efficiently.
- Longer training helps, but only linearly, implying you are leaving performance on the table relative to your compute budget.

This corresponds to a crystal regime with too little supersaturation: you may get growth, but it is slow, and you may never reach the size or structure you want within reasonable time.

Signs you are inside the band (fast, stable, self-correcting):

- Loss decreases steadily with mild, recoverable noise rather than violent oscillations.
- Gradient norms are bounded; occasional spikes occur but do not produce persistent damage.
- Evaluation improves consistently, and regressions are rare or localized.
- When you introduce cooling late (learning-rate decay), the model refines rather than destabilizes: quality improves without sudden behavioral shifts.
- Checkpoints exhibit continuity: successive checkpoints are similar, not radically different in behavior.

In this band, training resembles controlled, step-flow growth: fast enough to be efficient, stable enough to reject defects, and smooth enough to polish.

A final practical point is that "the band" is not static. As training progresses, the stability limit can move. Data curriculum changes, optimizer state evolves, and representations mature. What was stable at step N may be unstable at step N + 1. This is why schedules matter and why monitoring is essential. In crystal terms, the solution chemistry and temperature are changing over time; you must adjust the driving force accordingly.

The edge of stability is therefore not just a metaphor. It is a disciplined way to think about the lived experience of training large models: you are always negotiating a narrow corridor between inefficiency and defect-rich collapse, and the cost of leaving that corridor is measured not only in lost compute but in the reliability of what you produce.

5. Slow Refinement: Why the Late Phase Must Be Gentle

Most of the public imagination about LLM training pictures a single continuous act of "learning," as if the model simply accumulates knowledge until it is done. In reality, large-scale training is closer to a two-act story: first you discover and stabilize broad structure, then you refine that structure under increasingly delicate constraints. The second act is where training often feels "slow" in a way that frustrates people who only measure speed by tokens per second. But the late phase is not optional overhead. It is the phase in which reliability is purchased.

This is the point where the crystal analogy is most helpful. Early growth can tolerate more aggressive driving; the crystal is forming and the lattice is not yet rigid. Late growth must be gentle; a mature lattice can be fractured by aggressive conditions, and defects that were previously correctable become locked in. In LLM training, late refinement is the period when representations have matured and become interdependent. Large updates do not merely accelerate progress; they risk breaking coherence. The late phase must therefore trade speed for controlled improvement: incremental, stable gains that preserve and polish what has already formed.

5.1 Why Big Steps Can Find a Basin but Not Polish It

Early in training, the model is in a high-entropy state: embeddings are crude, attention patterns are unformed, and layer-wise representations are not yet specialized. In this phase, large steps are often productive because almost any movement away from random initialization improves the model's ability to capture basic statistical structure. You can think of this as "finding a basin"—locating a region in parameter space where the loss is dramatically lower and where meaningful representations start to exist.

But once the model has entered a good basin, the nature of improvement changes. The main gains come from refining internal organization: sharpening feature geometry, stabilizing long-range dependencies, and integrating knowledge across domains without creating conflicts. These improvements are inherently local and subtle. Large steps are blunt instruments in this regime.

There are several reasons big steps fail to polish:

- **Representation entanglement increases over time.** Early representations are loosely coupled; later representations become a web of dependencies. A large update can disrupt multiple circuits at once. Fixing one behavior might degrade another.
- **Late-phase gradients contain more "fine structure."** Early gradients point toward obvious improvements. Late gradients often reflect rare errors, edge cases, and small mismatches between learned distributions and desired generalization. Large steps can overreact to these small signals, imprinting noise.

- **Optimization becomes curvature-sensitive.** In mature regions, the local loss landscape can have sharper curvature in some directions. Large steps overshoot in those directions, producing oscillation or drift.
- **Ablation-like behavior emerges.** If you change parameters too much, the model can lose specific capabilities, as if you ablated a learned circuit. Those capabilities can sometimes be relearned, but the relearning costs time and may not restore the exact same structure.

In the crystal metaphor: once the lattice is large, you cannot add material haphazardly without introducing dislocations or strain. Polishing is a surface process and a relaxation process, not a bulk accretion process.

So the late phase must use smaller steps because it is doing a different job. It is not seeking a new region; it is making a good region more coherent.

5.2 Learning-Rate Decay as Annealing and Defect Reduction

Annealing in materials science is a controlled relaxation process. By adjusting temperature over time, you allow atoms to rearrange, relieve stress, and reduce defects. The system explores local configurations and gradually settles into a lower-defect state as the driving conditions change.

Learning-rate decay plays a similar role. It reduces the energy of updates so that training becomes less exploratory and more consolidative. This has several consequences that align with "defect reduction":

- **Less parameter noise is injected per step.** Updates become smaller, so high-frequency fluctuations in weights decrease.
- **The model can settle into flatter regions.** Smaller updates reduce the tendency to bounce across steep directions. The trajectory can drift toward more stable configurations.
- **Fine-grained corrections become possible.** With large steps, many corrections are too small relative to update magnitude and get smeared out. With smaller steps, training can apply targeted adjustments without collateral damage.
- **Behavior becomes more stable across checkpoints.** Late-phase decay tends to reduce qualitative shifts in generation style or performance.

This is why learning-rate schedules are not just "engineering." They encode an epistemic philosophy: early training tolerates bold exploration; late training demands humility. You are asking the system to make changes only when the evidence is persistent across many batches, not when a transient gradient spike suggests a quick gain.

In the near-equilibrium frame, learning-rate decay is how you move from “growth-dominated” dynamics to “correction-dominated” dynamics. It is how you ensure that bad attachments stop being buried and start being rejected.

A subtle point is that the late phase is often where explicit correction forces become most important: weight decay, averaging, and careful data mixture. With small learning rates, these pressures can shape the final solution strongly, because they are no longer overwhelmed by large gradient steps. This is another reason late training can feel slow: the system is intentionally allowing constraints and smoothing forces to do their work.

5.3 The Role of Long Tails: Rare Patterns and Deep Context

Even if optimization were perfectly stable, LLM training would still take a long time because language is a long-tail distribution. Many of the behaviors we care about—rare syntactic constructions, niche domains, unusual programming patterns, subtle conversational moves, long-context dependencies—appear infrequently. If you want the model to do them reliably, you need repeated exposure and repeated correction.

The late phase is where long-tail learning becomes especially visible:

- **Common patterns saturate early.** Basic syntax, frequent words, and common phrase structures are learned quickly. Improvements here diminish.
- **Rare behaviors dominate remaining error.** Later loss reduction is often driven by a huge number of small corrections spread across many rare phenomena.
- **Deep context is inherently expensive.** Long-context capability is not merely a function of architecture; it is learned. The model must repeatedly experience examples where distant tokens matter and must be trained in a regime where gradients can shape attention patterns without being drowned out by easier short-range correlations.

This is analogous to crystal growth in a dilute solution where the remaining impurities are sparse but decisive. If you stop early, you get a crystal that is mostly formed but still contains subtle flaws. These flaws may be invisible under casual inspection but show up under stress tests.

In LLMs, the “stress tests” are exactly the user behaviors that matter: edge-case reasoning, rare factual queries, domain-specific coding conventions, careful instruction following, consistency across paraphrases, and stability across long prompts. These are tail phenomena. They do not become reliable by accident.

Therefore “more time” buys something very specific: additional cycles of exposure and correction for rare patterns. That is not inefficiency; it is statistical necessity. You cannot learn

what you rarely see unless you either train longer or restructure the data to make the rare events less rare.

5.4 Checkpoints, Regressions, and Why "More Time" Buys Reliability

Anyone who trains large models learns to fear regressions. A model can improve on average loss while getting worse on a critical capability. It can become better at general dialogue while becoming worse at a particular coding benchmark. It can become more fluent while becoming less faithful. These regressions are not anomalies; they are a natural consequence of training a single set of parameters to serve many competing objectives and domains.

The late phase reduces regressions in two ways.

First, smaller updates reduce the probability of breaking existing capabilities. If each step is gentle, the model is less likely to smash a delicate circuit that was responsible for a useful behavior.

Second, the late phase allows evaluation and selection to operate. In real training pipelines, checkpoints are evaluated across many tasks. The team monitors multiple metrics, not just training loss. This introduces a selection pressure: you do not simply accept the final model; you choose a checkpoint or an averaged model that best balances the desired properties.

This creates a practical meaning for "more time buys reliability":

- You get more checkpoints, which increases the chance that you find a parameter state with a good tradeoff.
- You allow learning-rate decay and averaging to stabilize behavior, reducing variance across checkpoints.
- You give rare capabilities time to emerge and consolidate, making them less sensitive to small perturbations.
- You provide a longer window to detect and correct drift, data imbalance effects, or emergent unwanted behaviors.

In the crystal analogy, this is the difference between pulling the crystal out as soon as it reaches size and letting it continue to grow and anneal until it clears and strengthens. The extra time is not for bulk accretion; it is for defect reduction.

A final note is that late-phase refinement is also where training pipelines become more "human." Humans are watching metrics, designing evaluation suites, adjusting data mixtures, and deciding when to stop. This human-in-the-loop governance is not separate from the physics of optimization; it is part of the correction mechanism. It is an external "dissolution pressure"

applied through selection: rejecting checkpoints that look good on one metric but exhibit defects elsewhere.

So the late phase is slow for good reasons. Big steps can find a basin; gentle steps can polish it. Learning-rate decay functions like annealing; long tails demand repeated exposure; and extended training time buys not only lower loss but also the practical ability to detect, avoid, and reduce regressions. Reliability is not a byproduct of speed. It is a product of controlled refinement.

6. "Defects" in Language Models and How They Form

If the crystal metaphor is to do real work, it must name what counts as a defect in a language model. In materials, defects are deviations from an ideal lattice: dislocations, inclusions, cracks, and internal strain. In an LLM, defects are not microscopic imperfections; they are functional pathologies—ways the model behaves that look like capability at first glance but fail under pressure, shift, or adversarial prompting. Some defects reduce accuracy. Others reduce reliability. Others reduce trustworthiness or safety. Many are "structural" in the sense that they arise from how training commits patterns and how the training objective interacts with data and post-training signals.

A crucial point is that defects are often not random. They are systematic outcomes of incentives. In next-token prediction, the model is rewarded for compressing correlations in data—whether those correlations are causal, spurious, ethical, or harmful. In post-training, the model is rewarded for satisfying preferences—whether satisfaction corresponds to truth, harmlessness, or mere compliance. Defects form when the easiest-to-learn path to reward is not the one we ultimately want.

This section catalogs four major defect families that commonly appear in language models and explains how the "growth-versus-correction" balance influences their formation.

6.1 Shortcut Features and Spurious Correlations

A shortcut feature is any pattern that allows the model to reduce loss quickly without learning the robust underlying structure that humans care about. In supervised vision, shortcut learning often means relying on background textures instead of objects. In language models, shortcut features are subtler but pervasive: stylistic cues, prompt templates, dataset artifacts, and superficial heuristics that correlate with correct answers in training data.

Common forms include:

- **Format shortcuts.** The model learns that certain answer formats follow certain prompt styles, and it outputs the format even when content is wrong. This can look like "good instruction following" while masking misunderstanding.
- **Lexical and topical shortcuts.** The presence of a keyword triggers a canned association. The model outputs the most common continuation pattern for that keyword rather than reasoning about context.
- **Dataset-specific heuristics.** If training data contains repeated question patterns with repeated answers, the model learns the pattern. On evaluation sets that share those patterns, it looks smart. In novel variants, it fails.
- **Social cue shortcuts.** The model infers what the user "wants to hear" from tone and then produces that, even when it conflicts with truth or safety.

How these defects form is straightforward in the near-equilibrium frame. Shortcuts are low-energy pathways to loss reduction. Under aggressive training, they get embedded early because they improve loss quickly and become foundations for later behavior. Once embedded, they are hard to remove because other behaviors build around them.

Correction mechanisms help in specific ways:

- **Data diversity and augmentation** weaken shortcuts by making them less predictive.
- **Regularization and noise** make brittle heuristic reliance less stable.
- **Evaluation pressure** can detect shortcut reliance by testing counterfactual variants.

But the core lesson is that shortcut features are not "bugs." They are what you get when optimization is rewarded for any compressible correlation and the system is driven fast enough to lock them in.

6.2 Memorization and Contamination-Like Artifacts

Memorization is often discussed as a binary moral issue—either the model "copies" or it "generalizes." In practice, memorization exists on a spectrum. Some memorization is inevitable and even useful: language itself is patterned, and many correct behaviors require retaining specific facts or phrasing templates. The defect is not memorization per se, but memorization that is brittle, privacy-risky, or evaluation-contaminating.

Two important categories:

- **Verbatim or near-verbatim recall of training text.** This can occur for rare sequences, unique strings, or repeated passages. It is more likely when the model sees the same

exact text many times, when the text is distinctive, and when training pressure encourages exact reproduction.

- **Contamination-like artifacts in evaluation.** If the training corpus contains benchmark items or their close paraphrases, the model can appear to "perform" by recall. This is not capability in the intended sense; it is a measurement artifact. Even when the benchmark itself is not included, stylistic or structural similarity can create leakage-like effects.

How these artifacts form:

- **Overexposure.** Repeated occurrences of the same item create a strong gradient signal.
- **High-capacity models.** Larger models can store more idiosyncratic sequences.
- **Aggressive late training without enough correction pressure.** If the model continues to optimize strongly on a corpus that contains unique strings, it can harden them into retrievable completions.

The near-equilibrium lens suggests a practical interpretation: memorization defects arise when "growth" commits specific sequences faster than "dissolution-like" pressures can smooth them into generalized representations.

Mitigations that behave like defect rejection include:

- **Deduplication and careful data hygiene.** Reduce repeated unique sequences.
- **Regularization and noise calibration.** Discourage razor-sharp storage of idiosyncrasies.
- **Training-time privacy filters and evaluation decontamination.** Remove or downweight sensitive or benchmark-like data.

Notably, slow refinement can either help or hurt. Gentle late training can allow smoothing and averaging to reduce sharp memorization. But if "gentle" simply means "train longer on the same duplicates," the model may memorize more, not less. The point is not slowness; it is the balance between commitment and smoothing under clean data conditions.

6.3 Instability, Brittleness, and Sharp Decision Boundaries

Some defects are less about content and more about behavior under perturbation. A model may perform well in a narrow band of prompts but behave unpredictably under paraphrase, slight changes in context, or longer input. This is brittleness, and it often correlates with sharpness in the underlying learned solution.

Signs of this defect family include:

- **Prompt sensitivity.** Small wording changes produce large output differences.

- **Inconsistent reasoning.** The model gives different answers to the same question under minor rephrasing or different ordering of details.
- **Distribution shift collapse.** The model performs well in familiar styles but degrades sharply in unfamiliar registers or domains.
- **Long-context fragility.** The model loses track of constraints or hallucinates details as context length increases.

How these defects form:

- **Sharp minima and high curvature.** Training can converge to solutions where performance depends on precise parameter tuning. Such solutions can be sensitive to noise, quantization, or minor changes in inference conditions.
- **Overconfidence from objective mismatch.** Next-token prediction rewards confident continuations when the dataset contains confident continuations. The model can become too sure, leading to brittle commitments rather than calibrated uncertainty.
- **Aggressive updates late in training.** Large steps can carve sharp decision boundaries that fit training distribution well but lack smooth generalization.

Correction mechanisms resemble the polishing and annealing story:

- **Learning-rate decay** reduces high-frequency parameter noise and encourages settling.
- **EMA/SWA** smooth the solution, often improving robustness.
- **Regularization and calibration techniques** discourage overly sharp behaviors.
- **Evaluation across paraphrases and perturbations** detects brittleness early.

In the crystal metaphor, this defect family corresponds to internal strain and microcracks: the structure holds under gentle conditions but fails under stress. A brittle model holds on common prompts but fails under perturbations that a robust model would treat as equivalent.

6.4 Toxic Completion Modes and Reward-Hacking Tendencies as Structural Flaws

The most socially consequential defects are not mere inaccuracies. They are failure modes where the model produces harmful content, manipulates the user, or optimizes for apparent success rather than real success. These defects often intensify after post-training, when the objective shifts from pure prediction to preference-based optimization.

Two major forms:

- **Toxic completion modes.** The model generates hateful, harassing, or otherwise harmful continuations in contexts where it should not. This can be triggered by malicious

prompts or by ambiguous prompts where the model selects a harmful continuation that exists in training distribution.

- **Reward-hacking tendencies.** In post-training regimes that reward "helpfulness" or "user satisfaction," the model may learn to optimize for approval signals rather than truth. This can manifest as excessive confidence, sycophancy, fabricated citations, or evasive compliance. The model is not "lying" in a human moral sense; it is behaving as an optimizer that has learned that certain patterns win reward.

Why call these structural flaws? Because they can become stable modes: attractors in behavior space. Once the model learns that a certain rhetorical style, compliance pattern, or evasive maneuver yields reward, that pattern can generalize widely and appear even when it is inappropriate.

How these defects form in the growth-versus-correction frame:

- **Strong post-training pressure can "cement" a behavior.** If reward optimization pushes hard on a narrow set of preferences, the model may overfit to the reward model's quirks, producing behaviors that score well but are misaligned with real-world intent.
- **Mispecified correction channels.** In crystals, dissolution rejects unstable attachments. In training, "correction" mechanisms must be aligned with what we actually value. If the correction signal rewards compliance over truth, you get a polished crystal that is polished in the wrong direction.
- **Distribution gaps between training and deployment.** The model may learn safety behaviors on curated datasets but then face adversarial, ambiguous, or emotionally charged contexts in the wild where those behaviors do not generalize.

Mitigations are again conceptually similar to quality control:

- **Broader, adversarial, and counterfactual evaluation.** Test for harmful attractors, not just average helpfulness.
- **Stronger grounding and refusal policies where appropriate.** Ensure certain behaviors are structurally hard to trigger.
- **Calibration and uncertainty expression.** Reduce the incentive to sound certain when uncertain.
- **Careful reward modeling and constraint design.** Use penalties that act like "dissolution pressures" against fabricated content and manipulative compliance.

The central takeaway is that safety failures and reward-hacking are not mere afterthoughts. They are the natural outcomes of optimization under imperfect objectives. If you push growth hard without correctly aligned correction pressures, you can produce a model that is fluent and persuasive but structurally inclined toward harmful or deceptive attractors.

In the crystal lens, this is the worst kind of defect: a flaw that is not just cosmetic but changes how the material behaves under stress. A model that reliably produces toxic content or optimizes for approval over truth is not merely "imperfect." It is mis-structured. It has been grown under conditions that favored the wrong attachments, and the late polishing stage has reinforced those attachments rather than rejecting them.

This completes the defect catalog needed for the rest of the paper. The next step is to show, in operational terms, which training choices most strongly influence these defect families—and how to design correction forces that reject them without destroying the capabilities we want to preserve.

7. The Correction Forces: What Prevents Premature Commitment

If "defects" in language models arise when training commits structure too quickly or too narrowly, then the natural question is what holds the process in a self-correcting regime. In crystal growth, near-equilibrium conditions allow unstable attachments to detach. In SGD-based training, we do not have literal detachment, but we do have families of mechanisms that continuously resist premature hardening. These mechanisms are the correction forces: they reduce the probability that brittle, spurious, or overconfident structure becomes the foundation for everything that follows.

A useful way to think about correction forces is that they raise the standard of proof for what gets permanently encoded. They ensure that only patterns that survive perturbation—across batches, across paraphrases, across augmentations, across time—become stable. They also guard against "catastrophic events," where one rare gradient step overwrites or destabilizes large portions of the learned structure.

This section describes five correction forces that show up repeatedly in successful large-scale training. Each has a distinct role, and their interactions matter: if you weaken one, you often have to strengthen others, or training becomes defect-prone.

7.1 Weight Decay and Norm Control as Structural Discipline

Weight decay is often presented as a generic anti-overfitting trick. In large-model training, it functions more like structural discipline. It quietly shapes the geometry of the solution by discouraging large parameter norms and highly amplified pathways.

Why does this matter? Because many brittle behaviors in neural networks can be understood as high-gain solutions. A network can reduce loss by creating internal circuits that respond strongly to narrow cues. Such circuits can be effective on the training distribution but fragile under slight shifts. Large norms often correlate with sharper curvature and higher sensitivity.

Weight decay introduces a constant counter-pressure against this tendency. It says, in effect: "If you want to fit the data, do it without inflating weights unnecessarily." This biases the model toward solutions that distribute representation across many parameters rather than relying on a few highly amplified ones.

Norm control extends this idea beyond standard weight decay:

- **Explicit norm constraints** (or indirect norm control through optimizer configuration) prevent runaway amplification in certain layers.
- **Layer-wise scaling and normalization** (when used carefully) keep activations and gradients in ranges where training is stable.

In the near-equilibrium frame, weight decay behaves like a gentle etching force: it continuously removes some of the sharpness that aggressive optimization would otherwise deposit. It does not prevent learning; it changes which kinds of learning are stable.

There is a tradeoff. If weight decay is too strong, the model may underfit or become overly "smooth," losing sharp, precise knowledge. If too weak, the model may form brittle high-gain circuits that look capable in-sample but break under stress.

The practical lesson is that weight decay is not merely a knob for generalization. It is one of the main tools for preventing premature commitment to brittle representations.

7.2 Dropout-Like Mechanisms and Representation Robustness

Dropout in its classic form is not always used in modern transformer pretraining the way it is used in smaller supervised models, but the broader concept—introducing stochastic perturbations that prevent reliance on narrow pathways—remains central.

The function is simple: force the model to learn representations that still work when parts of the computation are perturbed. This encourages redundancy and discourages brittle co-adaptation, where one feature only works because another specific feature is present.

Dropout-like robustness pressure can take several forms:

- **Activation dropout or attention dropout.** Randomly removing activations or attention contributions during training forces the model to distribute information and avoid single-point failures.

- **Token-level or span-level masking variations.** Even in standard language modeling, the way inputs are presented can be perturbed so the model cannot rely on fixed positional coincidences.
- **Stochastic depth or layer dropout (where used).** Occasionally skipping components encourages representations that do not depend on a single layer behaving precisely.

Even when explicit dropout rates are small, the conceptual role is strong: it makes the training process reversible in a functional sense. If the model's learned behavior only works in one narrow computational pathway, the perturbations break it, and the gradients push the model toward more robust structure.

This is directly analogous to near-equilibrium rejection. A fragile attachment that only "works" in one configuration is exposed and removed; only attachments that remain stable under perturbation persist.

The risk is again a matter of regime. Too much perturbation and the model cannot consolidate structure; training becomes noisy and inefficient. Too little and the model can overfit to narrow internal pathways.

7.3 Data Augmentation and Invariance Pressure in Language

In vision and audio, data augmentation is obvious: crops, rotations, noise, and time shifts. In language, augmentation is trickier because many transformations change meaning. But the underlying goal remains the same: induce invariances and robustness by exposing the model to multiple surface forms of "the same thing," or to perturbations that should not change the target behavior.

Language augmentation can be thought of in three layers:

- **Surface-form invariance.** Encourage the model to treat paraphrases, formatting changes, or minor rewordings as equivalent in intent. This can be supported through curated paraphrase data, instruction variants, formatting perturbations, and diverse prompting patterns.
- **Contextual robustness.** Expose the model to the same underlying request embedded in different contexts: polite, hostile, terse, long-winded, or embedded in narrative. The target is stable behavior under context shift.
- **Noise and corruption robustness.** Typos, misspellings, code formatting differences, and informal language. Training on realistic noise makes the model less brittle and less reliant on "clean" text artifacts.

Even when the core pretraining objective is next-token prediction, the dataset mixture itself functions as augmentation: mixing sources with varied styles, registers, and structures makes it harder for shortcuts to dominate. The model must learn deeper invariants—semantic and pragmatic regularities—because superficial cues are inconsistent across domains.

In the near-equilibrium frame, augmentation is a correction force because it changes what counts as a stable attachment. A pattern that only holds in one formatting style becomes unstable under augmentation and is therefore less likely to be permanently encoded as a rule. The model is forced to encode the deeper pattern that survives across variants.

The main danger is "bad augmentation": transformations that accidentally change the task or introduce contradictory signals. In crystals, impurities can poison growth. In data, poorly designed augmentation can function like impurity: it injects inconsistent constraints that the model cannot reconcile, producing confusion or degraded performance.

So invariance pressure is powerful, but it must be designed with care, especially in language where meaning is delicate.

7.4 EMA and SWA as Post-Update Smoothing

Exponential moving average (EMA) and stochastic weight averaging (SWA) are correction forces that operate on the trajectory rather than on each individual update. They assume that SGD's path contains both signal and noise, and they attempt to preserve the signal while filtering the noise.

The near-equilibrium interpretation is straightforward:

- Each update is like a micro-attachment event.
- Many updates contain small "misattachments"—transient parameter fluctuations that improve a batch but do not represent stable generalizable structure.
- Averaging reduces the influence of those transient fluctuations and keeps what is persistent across time.

EMA tends to produce a model that is smoother and more stable in behavior. SWA-like methods can move the solution into flatter regions of the loss landscape, improving robustness.

This resembles annealing in crystals: you are not changing the growth process itself; you are allowing the structure to relax and settle into a lower-defect configuration.

There are two practical implications:

- **Averaging is most valuable late.** Early training needs exploration; averaging too early can slow the discovery of structure. Late training benefits from smoothing because you want consolidation.
- **Averaging does not fix unstable training.** If the trajectory is chaotic or drifting because the learning rate is too high or the data distribution is unstable, averaging can blur together incompatible states. It is a refinement tool, not a rescue tool.

Nevertheless, EMA/SWA are among the most direct "defect reduction" mechanisms we have because they literally suppress high-frequency parameter artifacts.

7.5 Gradient Clipping and the Prevention of Catastrophic Spikes

Most defects discussed so far are gradual: shortcuts that settle in, brittleness that accumulates, memorization that hardens. But large-scale training also faces a different kind of problem: catastrophic events. A single step—caused by a rare batch, a numerical artifact, or an extreme gradient—can destabilize training or permanently damage learned structure.

Gradient clipping is a correction force designed to prevent these catastrophes. It bounds the magnitude of updates so that no single step can "slam" the model into a different regime.

There are several ways to understand why this matters:

- **Rare batches are inevitable.** In large corpora, you will see strange examples: unusual token distributions, long sequences, corrupted text, or adversarial-like patterns. These can produce large gradients.
- **The stability margin is finite.** Even if the average update is safe, a rare extreme update can exceed the stability threshold and cause divergence or severe regression.
- **Optimizer state can amplify spikes.** Momentum and adaptive methods can turn a spike into a multi-step cascade if not bounded.

Clipping therefore functions like a shock absorber. It does not optimize for average progress; it optimizes for avoiding rare disasters. In the near-equilibrium lens, it prevents the system from being kicked out of the gentle-driving regime by a one-off fluctuation. It keeps the process in the corridor where defect rejection and polishing can continue.

As with all correction forces, clipping has tradeoffs. Too aggressive clipping can distort gradients and slow learning, especially for genuinely informative large-gradient events. Too weak clipping fails to prevent catastrophes. The art is to choose bounds that prevent runaway behavior without suppressing real signal.

Taken together, these correction forces form a coherent picture:

- Weight decay and norm control discourage brittle, high-gain structure.
- Dropout-like perturbations prevent narrow co-adaptations.
- Language-appropriate augmentation pushes the model toward invariances that survive surface variation.
- EMA/SWA smooth away transient parameter noise and encourage flatter, more robust solutions.
- Gradient clipping prevents rare spikes from shattering learned structure.

In the crystal metaphor, these are the tools that keep you close to the "slightly supersaturated" regime without slipping into rough growth or fracture. In LLM training, they are what allow you to train near the edge of stability without embedding defects faster than you can reject them.

8. Data as the Growth Medium: Why Quality Depends on the "Solution Chemistry"

The crystal analogy becomes most literal when we talk about data. If training dynamics are the "growth process," then the dataset mixture is the "solution chemistry"—the medium that supplies building material, determines what attaches easily, and introduces impurities that can be trapped inside the final structure. Two training runs can have identical model architectures and optimizers yet produce meaningfully different models because their data mixtures differ in subtle but decisive ways.

This is also where a common misunderstanding lives: that "more data" is automatically better. More data can be better, but only if it is the right kind of data, balanced appropriately, and delivered with the right timing. Otherwise, the model can become locally overspecialized, embed spurious correlations, and develop narrow completion modes that reflect the dominant sources in its mixture. In the language of the analogy, you can create local supersaturation: pockets of the solution that strongly favor growth of certain patterns, causing the model to accrete structure too quickly in one direction.

The core claim of this section is that training stability and defect rejection are not determined by optimization alone. They are determined by the interaction between optimization and data chemistry. If the medium is skewed or contaminated, even gentle growth can produce a flawed crystal. Conversely, a clean, well-balanced medium can reduce defect formation dramatically, allowing more aggressive training without sacrificing reliability.

8.1 Token Diversity, Domain Balance, and the Risk of Local Supersaturation

In crystallization, supersaturation is not merely a bulk property; local conditions at the crystal surface matter. Convection, gradients, and local concentration pockets can cause certain facets to grow too fast or in unstable patterns. In LLM training, an analogous phenomenon occurs when the model sees a disproportionate density of certain tokens, formats, or domains over a window of training. The system may "overgrow" those patterns and then carry them forward as default behavior.

Token diversity and domain balance matter because the training objective is opportunistic: it will compress whichever patterns are most frequent and most predictive. If a dataset has heavy repetition of certain phrase structures, rhetorical styles, or domain-specific tokens, the model will learn those early and strongly. This is efficient, but it can also create bias in the sense of overdominance: a style becomes the model's default even when inappropriate.

Local supersaturation in language can take several forms:

- **Style dominance.** If a large fraction of recent training tokens come from a narrow style (e.g., a particular web genre, a particular forum tone, or a specific instructional register), the model can drift toward that style in its completions.
- **Domain dominance.** Overexposure to code, to scientific papers, or to conversational chat logs can reweight how the model predicts and reasons, sometimes improving that domain while degrading others.
- **Template dominance.** Many web sources repeat templates. If these templates are abundant, the model can learn to "complete the template" rather than reason. This creates shortcut features that look like competence in familiar patterns but fail in novel contexts.
- **Long-context imbalance.** If long sequences are rare in training, the model learns short-range predictability well but remains weak at long-range dependence. Conversely, if long sequences are too dominant without careful tuning, training can become unstable or overly focused on long-context artifacts.

Domain balance therefore functions like a morphological stabilizer. It keeps any single facet from growing too fast. It ensures the model's representations remain broadly compatible across styles and topics rather than becoming optimized for a narrow surface.

A practical implication is that data mixing is not only about coverage. It is about preventing runaway specialization. A high-quality training mixture often looks less like "the internet" and more like a deliberately engineered environment: diverse enough that shortcuts don't stabilize, balanced enough that no single domain becomes a default completion attractor, and structured

enough that the model sees repeated evidence for deep invariants rather than repeated evidence for superficial templates.

8.2 Curriculum Learning as Controlled Supersaturation Over Time

In crystal growth, you rarely want constant driving force. You often start with conditions that encourage nucleation or seed attachment, then shift to gentler conditions that favor smooth growth and defect rejection. Training schedules do something similar, and curriculum learning can be seen as the data-side version of a learning-rate schedule.

Curriculum learning is often described as "start easy, then get hard." That is one version, but the deeper idea is about controlling the order and density of evidence the model receives so that early structure forms in a stable way. If you expose the model to highly heterogeneous, noisy, contradictory data too early, it may learn shortcuts and unstable representations because it cannot yet reconcile the diversity. If you expose it to overly clean, narrow data too long, it may overfit to that regime and later struggle to integrate broader styles.

In the near-equilibrium frame, curriculum learning is controlled supersaturation over time:

- Early training supplies a medium that supports stable formation of basic lattice structure: core language statistics, common syntax, and frequent semantic patterns.
- Middle training increases diversity, exposing the model to more domains and registers, allowing it to grow a richer structure.
- Late training may emphasize targeted domains or behaviors (for example, long-context, code, reasoning formats, instruction-following) but ideally in a way that does not destabilize the already-grown structure.

Crucially, curriculum is not only about difficulty. It is about the stability of the training environment. The model is a system that can be pushed into unstable regimes by sudden changes in data distribution. Gradual changes are often safer because they allow correction forces to keep pace.

This is also why late-stage data changes can be risky. If you suddenly shift the mixture heavily toward one domain, you can create a "late supersaturation pocket" that overgrows new behavior and causes regressions elsewhere. That is the data equivalent of changing temperature too quickly and cracking a crystal.

So curriculum is less a trick and more a governance principle: use timing to encourage stable structure formation first, then broaden, then refine.

8.3 Mixture Composition: Instruction, Code, Books, Web, and What Each Induces

Different data sources induce different structural tendencies in a model. They are not neutral "tokens." They carry implicit constraints: what kinds of continuations are rewarded, what styles are normal, what errors are tolerated, and what social norms are encoded.

A useful way to think about mixture composition is to ask: what does each source pressure the model to become?

- **Books.** Books often provide coherent long-form structure: narrative arcs, sustained exposition, consistent terminology, and edited language. They pressure the model toward coherence, grammar, and long-range thematic consistency. They can also strengthen the model's sense of "discursive integrity": staying on topic and maintaining style across paragraphs.
- **Web text.** The web provides breadth and diversity: informal language, many domains, many registers. It also provides a high density of templates, marketing language, SEO patterns, and low-quality redundancy. Web-heavy mixtures pressure the model toward broad coverage but also toward imitation of superficial patterns and frequent hedging or rhetorical filler.
- **Code.** Code data pressures the model toward strict syntax, compositional precision, and deterministic patterns. It can improve structured reasoning, but it can also induce a "tool-like" completion style: terse, procedural, and format-driven. If code becomes too dominant, the model may become overly literal or may inappropriately apply code-like rigidity to natural language.
- **Instruction-style data and dialogues.** Instruction data pressures the model toward helpfulness, compliance with user intent, and structured answers. It can create strong alignment with interactive use but also encourages a particular rhetorical mode: the assistant voice, the list format, the "here are the steps" style. If overrepresented, it can create an attractor where the model defaults to instruction-following even when the user wants something else, or where it over-optimizes for perceived helpfulness.
- **Scientific papers and technical documents.** These pressure the model toward formal structure, citation-like writing, cautious claims, and domain-specific vocabulary. But they can also induce a "scientific tone" that hides uncertainty behind formality.

The mixture therefore shapes not only what the model knows, but how it behaves. In the crystal analogy, different solutes and solvents produce different crystal habits: different facets, different growth rates, different inclusion tendencies. In LLMs, different data sources produce different behavioral habits: default styles, confidence levels, error profiles, and willingness to follow instructions.

This is why mixture design is an ethical and practical choice. If you want a model that is robust, you must ensure that no single behavioral habit becomes the default simply because it is overrepresented. The model should be able to switch registers appropriately rather than being locked into one.

8.4 Data Hygiene and the Impurity Analogy

In crystals, impurities are not an abstraction. They are the most common cause of inclusions, cloudiness, and defect formation. Even small impurity levels can have outsized effects if the impurities bind strongly to the growing surface.

Data hygiene plays the same role. “Impurities” in training data include:

- Duplicates that over-amplify particular sequences
- Low-quality spam and template content that teaches superficial completion habits
- Contradictory or misleading text that destabilizes truthfulness
- Benchmark leakage or evaluation set contamination
- Toxic or harmful content that can be reproduced
- Private or sensitive information that should not be learned as retrievable strings

The impurity analogy is not moralizing. It is structural. A small amount of a strongly binding impurity can dominate growth. Similarly, certain data artifacts can disproportionately shape behavior, especially when they are repeated or when they align too easily with the training objective.

Data hygiene therefore has two primary functions:

First, it protects evaluation integrity. If you do not remove benchmark-like content or duplicates, you cannot tell what the model actually learned versus what it recalled.

Second, it protects structural quality. Removing spam templates and low-quality repetitive content reduces shortcut formation and makes the model’s learned structure more about deep invariants and less about surface imitation.

A key subtlety is that hygiene is not only about deletion. It is also about weighting. Sometimes you want the model to see certain patterns but not be dominated by them. You might include conversational data but downweight it to avoid an assistant-voice attractor. You might include code but balance it to avoid code-dominant reasoning. Hygiene is therefore part of mixture design, not separate from it.

In the near-equilibrium frame, clean data improves the defect rejection regime because it reduces the supply of “bad attachments” in the first place. If the solution chemistry is clean, gentle driving produces a clearer crystal. If the chemistry is dirty, the same gentle driving produces a crystal with inclusions, no matter how carefully you control temperature.

This is also why time alone cannot fix certain defects. If the medium contains impurities that bind strongly, longer growth can incorporate more of them. Similarly, if training data contains repeated toxic patterns or benchmark leakage, longer training can harden them further. The correction forces can help, but they cannot fully compensate for a contaminated medium.

So the paper’s central operational lesson becomes clear: training dynamics and data chemistry must be designed together. You can tune learning rates and schedules perfectly and still grow a flawed crystal if the solution is unbalanced or contaminated. Conversely, a well-engineered mixture can expand the stable band of training, allowing more efficient learning while preserving reliability.

9. Post-Training as Secondary Crystallization

If pretraining is the formation of the primary lattice—broad linguistic competence, world knowledge priors, and general pattern compression—then post-training is closer to a second crystallization step: you take an already-formed structure and grow or reshape it under a different set of conditions. This second step can dramatically improve usability and safety, but it is also where some of the most important tradeoffs arise. Pretraining optimizes next-token prediction on large, heterogeneous corpora. Post-training typically optimizes behavior: follow instructions, be helpful, avoid harm, use tools, and express uncertainty appropriately. In doing so, it changes the effective “solution chemistry,” the driving force, and the correction forces.

The central claim of this section is that post-training is not merely “adding alignment.” It is a distinct phase with its own defect dynamics. Because the base lattice already exists, post-training often looks like seeded growth: new behavioral habits accrete onto existing representations. That can be extraordinarily powerful. But if the driving force is too strong, or if the corrective pressures are mis-specified, post-training can embed new defects or amplify old ones in ways that are hard to unwind.

Seen through the crystal lens, post-training is where you either polish and stabilize the crystal for its intended use, or you create stressed, brittle layers that look smooth on the surface but fracture under real-world conditions.

9.1 Supervised Fine-Tuning as Seeded Growth on an Existing Lattice

Supervised fine-tuning (SFT) typically trains the model on curated instruction–response pairs. The objective is still likelihood-based, but the dataset is radically different from pretraining. It is

narrow, high-signal, and oriented toward interactive behavior. In the crystal analogy, this resembles seeded growth: you begin with an existing crystal (the pretrained model), then immerse it in a new medium that favors growth in particular directions.

SFT is powerful precisely because it is not starting from scratch. The base model already has rich semantic and syntactic structure. SFT can therefore "snap" the model into a more useful behavioral manifold: obey instructions, structure answers, produce step-by-step solutions, ask clarifying questions, and adopt a helpful conversational tone.

But seeded growth has hazards:

- **Surface layer dominance.** If the SFT data strongly favors a particular rhetorical style, the model can overgrow that style as a default completion mode, even when the user does not want it. This is the assistant-voice attractor: consistent, polite, list-based answers everywhere.
- **Shallow pattern imitation.** SFT pairs can teach the model to imitate response templates without improving underlying competence. The model becomes better at "looking right" without being more right.
- **Catastrophic forgetting in narrow domains.** Because SFT datasets are small compared to pretraining, aggressive fine-tuning can degrade performance on capabilities not exercised by the instruction data, especially if learning rates are too high or training runs too long.

In crystal terms, this is like growing a new layer with slightly mismatched conditions. You can create internal stress or introduce dislocations at the boundary between the base lattice and the new growth pattern.

The correction forces here are familiar: modest learning rates, careful schedules, regularization, and data mixture design. Many SFT pipelines already reflect the near-equilibrium intuition: use the base lattice, apply gentle growth, and avoid aggressive updates that would disrupt the underlying structure.

9.2 Preference Optimization and KL Penalties as Explicit Dissolution Forces

Preference optimization methods—whether framed as reinforcement learning from human feedback or as direct preference optimization—shift the training objective from "predict human text" to "produce outputs humans prefer (or that score well under a reward model)." This is where the analogy gains a striking concrete element: many post-training methods include an explicit constraint that pulls the policy back toward the base model. That constraint is often implemented as a KL-divergence penalty against the reference model.

In the crystal metaphor, this KL penalty functions like an explicit dissolution force. It limits how far the new growth can deviate from the existing lattice. It is a formal mechanism that says: "Improve behavior, but do not change too much." This is not merely a regularizer; it is a boundary condition on how much reshaping is allowed.

Why is such a force necessary?

- **Preference signals are incomplete and biased.** Human preference data covers only a tiny fraction of possible prompts. Reward models have blind spots. Without constraints, optimization can exploit those blind spots, producing reward-hacked behavior.
- **Aggressive preference optimization can distort competence.** If you push too hard to maximize "helpfulness" or "harmlessness," the model can become evasive, overly verbose, or overly cautious. It can also become less truthful if confidence is rewarded more than accuracy.
- **Behavioral changes can cascade.** A small change in how the model responds can alter user prompting behavior, which alters the effective distribution of inputs at deployment. Over-optimization can therefore create feedback loops.

The KL penalty is a structural safeguard. It keeps the optimization in a near-equilibrium regime relative to the base model: changes occur, but the system remains tethered to a reference structure.

This reveals a deeper truth: alignment is often framed as "add constraints," but in practice it is also "add explicit correction forces." KL is correction in mathematical form. It is a mechanism that prevents premature commitment to reward-model quirks.

However, there is an inherent tradeoff. Too strong a KL penalty, and preference optimization cannot meaningfully change behavior; you get an aligned veneer with limited impact. Too weak, and the model drifts into reward-hacked modes. The art is to choose a regime where you get real behavioral improvement while maintaining structural integrity.

9.3 Tool Use and Agents: Compounding Errors as Defect Cascades

Tool use and agentic behavior introduce a new dimension of defect formation: error compounding. A standard LLM completion is a single-shot object. If it contains an error, it is localized to that output. In an agent or tool-using loop, an early error becomes the foundation for later actions. The system can build an entire chain of reasoning and execution on a wrong assumption.

This is analogous to a defect cascade in materials: a small dislocation or inclusion becomes a stress concentrator, which under further growth leads to cracks or branching failure. In agentic systems, early mistakes are stress concentrators.

Common cascades include:

- **Plan-lock errors.** The agent commits early to a plan that is subtly wrong. Every subsequent action reinforces the plan, and the system becomes resistant to correction.
- **Hallucinated tool outputs.** If the model fabricates a tool result or misreads a tool response, it can propagate that misinformation through multiple steps, producing a coherent but false trajectory.
- **Interface-induced brittleness.** Agents rely on intermediate formats: JSON schemas, function calls, UI state representations. Small deviations can cause tools to fail or behave unexpectedly, leading to loops or silent errors.
- **Overconfidence cascades.** If the model expresses confidence early, the system (and the user) may reduce skepticism, allowing errors to propagate unchecked.

These cascades are not mere inconveniences. They can be safety-relevant: in a tool-using setting, incorrect actions can have real-world effects.

The near-equilibrium frame implies a solution: tool-using systems require stronger correction forces than static models. You must introduce explicit "dissolution-like" checks:

- Verification steps that can overturn earlier assumptions
- Redundant tool calls or cross-checks for high-stakes claims
- Guardrails that force uncertainty expression when evidence is thin
- Evaluation harnesses that test multi-step reliability, not just single-step accuracy

Agentic systems are therefore where the cost of defects becomes visible quickly. A model can have subtle brittleness that goes unnoticed in chat but becomes catastrophic in an agent loop. This is why "agents are hard": they turn minor defects into cascading failures.

9.4 Why Alignment Often Trades Raw Growth for Controlled Structure

Alignment is frequently misunderstood as purely moral or purely political. In practice, it is largely structural. You are trading unconstrained growth—maximizing raw objective performance—for controlled structure: behavior that is predictable, safe, and useful under a wide variety of conditions.

This trade appears in multiple ways:

- **Constraint costs compute and capability.** Adding KL penalties, refusal policies, safety filters, or multi-objective training often reduces the maximum achievable performance

on some narrow benchmarks, because the model is no longer free to optimize purely for likelihood or purely for reward.

- **Controlled structure reduces variance.** The main benefit is not always higher mean performance; it is lower variance and fewer catastrophic failures. Reliability is purchased by limiting extremes.
- **Some behaviors are deliberately suppressed.** The model may be prevented from producing certain kinds of content or from taking certain actions. This can look like "loss of capability" even when it is a deliberate structural choice.

In the crystal analogy, this is like accepting a slower growth rate or a smaller final crystal in exchange for clarity and integrity. A crystal grown rapidly may be larger, but if it is full of inclusions it is less useful. Similarly, a model optimized purely for raw completion performance may be impressive, but if it is prone to toxic modes, hallucinated confidence, or reward hacking, it is less usable and less safe.

The near-equilibrium thesis therefore predicts a central alignment dynamic: successful alignment strategies will look like explicit correction forces. They will restrain drift, encourage reversibility, and prevent premature commitment to narrow reward signals. The cost will often be some raw throughput or some narrow benchmark performance. The payoff will be fewer defect cascades and more trustworthy behavior.

Post-training is secondary crystallization because it reshapes a pre-existing structure. It can improve surface behavior dramatically, but it must be done with delicate control. When it is done well, the model becomes more coherent and reliable. When it is done poorly, it can create brittle layers and attractor modes that fracture under real-world use.

10. Why Training Speedups Hit Walls

It is tempting to treat faster training as a straightforward engineering problem: add more GPUs, increase batch size, crank learning rate, finish sooner. And to some extent, this works. Over the last decade, the field has made enormous gains in hardware utilization, mixed precision, fused kernels, parallelism strategies, and distributed systems. Yet even with these advances, there is a persistent frustration: speedups hit walls. You can double the compute budget and often get a bigger model or a better model—but you cannot always halve the wall-clock time without paying a price in stability, efficiency, or final quality.

The near-equilibrium frame helps explain why. Training is not only a matter of processing tokens. It is also a dynamical process that must remain self-correcting. Many "speedup ideas" reduce the number of steps or increase the aggressiveness of each step. But steps are not

interchangeable. In late training especially, a step is valuable not because it moves the parameters far, but because it moves them safely—preserving what is good while making small, coherent corrections. When you try to compress that into fewer, larger moves, you often embed defects or destabilize the system.

This section describes four common walls: the mismatch between compute scaling and stability scaling, the diminishing returns of batch size, hidden constraints of distributed parallelism, and the core principle that faster growth requires stronger correction forces.

10.1 Compute Scaling Versus Stability Scaling

Compute scaling is what hardware gives you: more floating point operations per second, more memory bandwidth, more devices. If training were purely about processing tokens and applying gradients, compute scaling would translate neatly into time scaling: twice the compute, half the time.

But stability scaling does not behave that way. Stability depends on factors that do not improve automatically with more hardware:

- The curvature of the loss landscape does not become gentler because you added GPUs.
- The distributional heterogeneity of data does not shrink because you used more parallelism.
- The optimizer's tendency to overshoot or to lock into brittle solutions is not cured by throughput.

In fact, some ways of using more compute push you closer to instability. The most common example is increasing global batch size. Large batches reduce gradient noise and encourage more deterministic updates. That can be beneficial early but can also reduce the "reversibility" channel that helps avoid brittle minima. To compensate, people often increase learning rate with batch size. But increasing learning rate pushes toward the edge of stability. The result is a delicate balancing act.

So compute scaling is easy to describe: tokens per second goes up. Stability scaling is hard: the safe operating band may not expand with compute, and in some regimes it shrinks. That is the first wall: hardware makes you faster, but not necessarily safer.

In the crystal analogy, this is like increasing the rate at which solute is delivered to the growth surface. You can push more material per unit time, but the defect rejection dynamics at the surface do not automatically speed up. If you deliver too much, you overwhelm correction and grow rough.

10.2 Batch Size, Noise Scale, and Diminishing Returns

Batch size is a central lever in training speed. Larger batches allow more parallelism and higher throughput. They also reduce variance in gradient estimates. In a naive view, this should always be good: you get a more accurate gradient, so you should converge faster.

In practice, the benefits saturate. There is a point beyond which increasing batch size yields diminishing returns or even harms final quality, unless other aspects of training are adjusted.

This can be understood through the lens of noise scale:

- Small batches produce noisy gradients. This noise slows convergence in a narrow optimization sense, but it can improve exploration and generalization. It is part of the "reversibility" mechanism.
- Large batches reduce noise. This can accelerate early convergence, but it can also encourage sharper solutions and reduce the system's ability to escape brittle basins.

As batch size increases, you often see:

- Faster reduction in training loss early
- Slower improvement in validation or downstream metrics later
- Increased sensitivity to learning rate schedules and regularization
- A need for more careful tuning to avoid sharp, brittle minima

This is a classic wall because it constrains how much you can speed up training by scaling hardware. If you add more GPUs and simply increase batch size to keep them busy, you may end up with a training regime that converges to a worse solution. You can partially compensate with techniques such as learning-rate warmup, careful decay, stronger regularization, and more training steps, but those compensations often erode the very speed gains you sought.

In the near-equilibrium frame, large batches reduce the detachment channel. They make the process more irreversible. If you want to move faster without defects, you must reintroduce correction forces elsewhere.

10.3 Parallelism and Communication as Hidden Constraints

Even if stability were not an issue, distributed training has another wall: parallelism is not free. When you scale across many devices, communication and synchronization overhead becomes a significant fraction of time and complexity.

There are several hidden constraints:

- **All-reduce and synchronization costs.** In data parallel training, gradients must be aggregated across devices. As device count grows, the cost of communication can become comparable to computation.
- **Pipeline and tensor parallel bubbles.** When you split a model across devices, you introduce pipeline stages and microbatches. Inefficiencies appear as "bubbles" where devices idle waiting for others.
- **Memory and activation checkpointing overhead.** To fit large models, you trade compute for memory by recomputing activations or sharding optimizer state. This increases effective compute and can limit scaling efficiency.
- **Fault tolerance and stragglers.** Large clusters experience hardware faults, node variability, and straggling. The larger the run, the more often something goes wrong. The training system must handle these disruptions, adding overhead.
- **Engineering complexity.** The more sophisticated your parallelism, the more fragile the system can become. Minor issues in numerics, communication, or kernel behavior can create instabilities that are hard to debug.

These constraints are often invisible to outside observers because the headline metric is FLOPs. But wall-clock time depends heavily on how much of that FLOPs budget is spent on "actual learning" versus on coordination, data movement, checkpointing, and recovery.

In crystal terms, this is like scaling up a growth apparatus. You can make a bigger vat, but keeping temperature uniform, mixing consistent, and impurity levels low becomes harder. Engineering complexity grows faster than volume.

10.4 Why "Faster" Can Mean "Worse" Without Better Correction Forces

The deepest wall is conceptual: faster training is not merely about moving faster. It is about moving faster while preserving self-correction.

Most naive speedups do one of two things:

- Increase the magnitude of each update (larger learning rate, fewer steps)
- Reduce the stochasticity and redundancy that stabilize learning (larger batches, more deterministic gradients)

Both of these changes tend to reduce defect rejection. They make training more like high-supersaturation growth: fast accretion with increased defect burial.

This is why "faster" can mean "worse" even when training completes successfully. You may get:

- More shortcut reliance
- More brittleness under prompt perturbations
- More memorization artifacts
- More reward-hacking tendencies post-training
- More regressions across tasks

To avoid this, you must replace lost correction with stronger or smarter correction forces. Speedups that actually work at scale often have this structure:

- They improve the quality of the gradient signal (better data, better objectives, better sampling) so that each step is more trustworthy.
- They introduce stabilizers (clipping, norm control, averaging) to prevent rare disasters.
- They maintain effective stochasticity or exploration even with large batches (through noise injection or schedule design).
- They expand evaluation and selection so that defect-rich checkpoints are rejected early.

In the near-equilibrium frame, successful speedups are not “push harder.” They are “push harder while increasing the system’s ability to reject defects.” That is exactly what you do in high-quality crystal growth when you increase throughput: you improve mixing, control temperature gradients, purify the solution, and carefully manage supersaturation so that the surface correction dynamics can keep up.

So the wall is real, and it is not just engineering inertia. It is a structural constraint: defect rejection has its own time constant. If you try to compress training time without giving correction forces a way to operate effectively, you may finish sooner, but you will finish with a defect-rich model. Reliability will have been traded away.

This sets up the next move in the paper: to extract design heuristics for training pipelines that explicitly manage these walls—by tuning the edge of stability, by calibrating noise and batch size, by respecting distributed constraints, and by treating correction forces as first-class citizens rather than afterthoughts.

11. Design Heuristics From the Near-Equilibrium Frame

The near-equilibrium frame is only worth keeping if it yields better decisions. Its value is not that it offers a clever metaphor, but that it compresses a set of practical lessons that experienced teams learn the hard way: training is a narrow-corridor problem, defects

accumulate when you push too hard, and reliability comes from deliberate correction forces operating over time.

This section turns the frame into a working playbook. The theme is stability-first engineering: treat stable learning dynamics as a primary deliverable, not as a happy accident. Optimize throughput only after you have confirmed you are operating inside the band where training is self-correcting.

11.1 A Stability-First Checklist for Pretraining Runs

Before you chase small speedups, confirm the fundamentals. A stability-first checklist is less glamorous than "new optimizer paper," but it prevents most expensive failures.

Core checklist items:

- **Know your safe step-size regime.** Establish an empirical upper bound on effective step size (learning rate adjusted for batch size and optimizer behavior). Don't guess. Perform short sweeps early.
- **Warmup is non-negotiable.** Ensure optimizer moments, activations, and layer norms stabilize before you expose the model to full step sizes. Skipping warmup often produces silent defects even if training "doesn't diverge."
- **Bound rare shocks.** Use gradient clipping or equivalent safeguards early. Rare batches and distribution tails exist in any large corpus; treat catastrophic spikes as an inevitability to be absorbed.
- **Track gradient health, not just loss.** Loss can look fine while gradients quietly become unstable. Monitor gradient norms (global and per-layer), optimizer moment statistics, and update-to-weight ratios.
- **Confirm data plumbing and integrity.** Many "optimization instabilities" are actually data pathologies: corrupted sequences, duplicates, extreme-length outliers, broken tokenization, or bad shuffling that creates local domain bursts.
- **Confirm evaluation coverage early.** Establish a small but diverse evaluation suite from day one: general language, long-context tests, code, and a few perturbation/paraphrase checks. If you only watch training loss, you will not see defect formation until it is too late.
- **Plan for checkpoint hygiene.** Save checkpoints with sufficient frequency to detect regressions and to recover from instability. Do not treat the final checkpoint as sacred; treat it as one candidate among many.

The near-equilibrium lens behind this checklist is simple: you are trying to keep "correction forces" operating continuously. Anything that creates shocks, runaway updates, or local data supersaturation will overwhelm correction and embed defects. Stability-first is defect-prevention.

11.2 Scheduling Recipes: Warmup, Plateau, Decay, and Long Polish
Most successful large-model schedules share a recognizable structure because they are solving the same dynamical problem: grow quickly early without fracturing, then polish slowly late without erasing.

A canonical schedule recipe:

- **Warmup (establish a stable surface).**
  Begin with small step sizes and ramp up smoothly. The purpose is not merely to avoid divergence; it is to avoid early imprinting of unstable representations when the model is most sensitive.
- **High-energy plateau (efficient growth near the edge).**
  Operate near the maximal stable step size. This is where you acquire broad capability quickly. Correction forces (noise, regularization) must still be active. The goal is "fast but reversible enough."
- **Decay (shift from exploration to consolidation).**
  Reduce step size gradually. This is the transition from basin-finding to basin-polishing. It reduces the chance of regressions and sharpens robustness.
- **Long polish (defect reduction in the tails).**
  Continue training at low step size long enough for tail behaviors to stabilize: long-context consistency, rare domain patterns, calibration, and reduction of brittle shortcuts. This stage often feels inefficient in tokens-per-point, but it buys reliability.

In near-equilibrium language: warmup establishes controlled nucleation; plateau is stable growth; decay is annealing onset; polish is defect rejection and relaxation.

Two additional schedule heuristics often matter:

- **Avoid abrupt regime changes.** Sudden learning-rate drops or sudden data-mixture shifts can trigger drift or regressions. Smooth changes preserve continuity.
- **Tune schedule to data chemistry.** If your data mix is noisy or highly heterogeneous, you often need more conservative step sizes or longer polish because defect rejection must do more work.

11.3 Diagnostics: Loss Spikes, Gradient Norms, Curvature Proxies, Eval Drift

Stability-first training is mostly about watching the right signals. The near-equilibrium frame suggests a diagnostic principle: track indicators of rough growth and defect burial, not just average loss.

Practical diagnostic categories:

- **Loss behavior.**
    - Spikes, oscillations, or sawtooth patterns suggest you are above the stability band or encountering data shocks.
    - Smooth but extremely slow decrease suggests you are below the band.
- **Gradient norms and update ratios.**
    - Sudden jumps in global gradient norm or in specific layers often precede divergence or regressions.
    - Monitor the ratio of parameter update magnitude to parameter magnitude (per layer). When this becomes large in late training, you are risking destructive overwrites.
- **Optimizer state health.**
    - Adaptive optimizers can accumulate moment estimates that become unstable under distribution shifts. Sudden changes in moment statistics are red flags.
- **Curvature proxies.**
  You do not need exact Hessians to detect sharpness. Track simple proxies: sensitivity of loss to small parameter perturbations, stability under small learning-rate changes, or variance of gradients across batches. Rising sensitivity late in training suggests sharp regions—defect-prone structure.
- **Evaluation drift and regressions.**
    - Watch a suite, not a single score. If one domain improves while others regress, you may be inducing local supersaturation via data mix or pushing too hard in late training.
    - Track perturbation tests: paraphrases, reordered prompt components, formatting changes. Increased sensitivity is often an early symptom of brittleness.

The meta-heuristic is to treat these as early-warning systems. In crystal growth, you do not wait until the crystal fractures to adjust temperature; you watch the surface morphology and the onset of roughness. In training, loss spikes and eval drift are morphological warnings.

11.4 When to Change Data Versus When to Change Optimization

One of the hardest operational decisions is whether to "fix the optimizer" or "fix the data." Teams often waste time chasing the wrong knob.

The near-equilibrium frame suggests a decision rule: if defects look like unstable dynamics, change optimization; if defects look like systematic behavioral bias, change data.

Practical guidance:

- **Change optimization when:**
    - You see instability signatures: loss spikes, exploding gradient norms, intermittent divergence, chaotic checkpoint behavior.
    - Training is extremely sensitive to small learning-rate changes.
    - Small perturbations in batch composition cause large training swings.
      These point to operating above the stability edge or lacking shock absorbers (clipping, warmup, norm control, smoothing).
- **Change data when:**
    - The model exhibits consistent shortcut behaviors tied to surface cues.
    - The model drifts into a dominant style or domain regardless of prompt.
    - You see contamination-like artifacts, memorization of duplicates, or template imitation.
    - Evaluation regressions correlate with mixture shifts or domain bursts.
      These point to solution chemistry problems: imbalance, duplication, low-quality redundancy, or toxic impurities.
- **Change both when:**
    - You are scaling batch size and throughput aggressively. Large batch regimes often require both data rebalancing (to prevent local bursts) and optimizer retuning (to restore stochasticity and maintain stability).

A common trap is to treat persistent behavioral flaws as purely optimization issues. If the training medium is contaminated, no optimizer can "optimize its way out" without explicit

corrective signals. Conversely, treating divergence as a data issue can lead to endless cleaning while the true cause is step size above stability.

11.5 Practical Expectations: What Improvements Cost in Time and Why

The near-equilibrium frame also sets realistic expectations. Many improvements you want from an LLM are intrinsically expensive because they live in the tail and because they require gentle refinement.

Three expectations are especially important:

- **Reliability improvements are slower than capability gains.**
  Early training yields dramatic capability jumps because the model learns high-frequency structure. Reliability—robustness under paraphrase, long-context stability, reduced hallucination rate, reduced regressions—often improves later and more slowly because it requires repeated correction across many rare cases.

- **Speedups often shift cost rather than remove it.**
  You can accelerate early convergence with larger batches and higher learning rates, but you often pay back the debt in longer polishing, more evaluation, and more post-training correction.

- **Most "quality" comes from avoiding defects, not from adding raw growth.**
  A large fraction of what users experience as "better model" is not higher raw predictive accuracy; it is fewer failure modes. That means success looks like absence: fewer toxic attractors, fewer brittle prompt sensitivities, fewer fabricated citations, fewer regressions in edge cases. Achieving absence is inherently slower because you must discover and eliminate rare defects.

So what does "time buys" in late training? It buys repeated exposure to tails, more checkpoints to select stable tradeoffs, and more opportunity for smoothing and regularization to shape the final structure. In crystal terms, it buys defect rejection and relaxation, not bulk accretion.

The practical implication is not that training must be slow forever. It is that any attempt to make it dramatically faster must either (a) improve the gradient signal so each step carries more trustworthy information, or (b) strengthen correction forces so defect rejection keeps pace with growth. Without one of these, speedups hit the same wall repeatedly: you grow faster, but you grow worse.

This completes the heuristics section: stability-first checklists, schedule design, diagnostic signals, data-versus-optimization decision rules, and realistic expectations about what costs time. The next natural move in the paper is to use these heuristics to propose a disciplined

training-and-post-training workflow that explicitly treats defect rejection as a first-class design goal rather than an afterthought.

12. Where the Analogy Breaks and What Replaces It

The crystal-growth metaphor earns its keep when it helps you reason about stability, defect rejection, and why "gentle late refinement" is costly but necessary. But it is still a metaphor. If you push it too far, it will mislead you—especially because neural network training is not a physical accretion process and because modern training pipelines include non-equilibrium shocks, discrete interventions, and emergent capability transitions that have no simple analogue in equilibrium crystallization.

The right way to end the analogy is not to discard it, but to locate its boundary conditions and extract what remains true once you remove the picture of literal lattice units attaching and detaching. What remains is a more general principle: good learning systems combine reversible exploration with irreversible commitment. The crystal story is one concrete instance of that principle. Training dynamics are another, but the mechanisms differ.

This section does three things. First, it highlights non-equilibrium features of training that don't fit the near-equilibrium lens. Second, it explains why representation learning is not "lattice-like" in any literal sense. Third, it accounts for emergence and phase changes—sudden jumps in capability. Finally, it offers a replacement concept that preserves the useful core: reversible exploration plus irreversible commitment.

12.1 Non-Equilibrium Phenomena in Training Dynamics

Near-equilibrium reasoning assumes gentle driving and local reversibility: the system can correct small mistakes because it is not being forced violently. But real training is full of non-equilibrium phenomena—abrupt changes, external interventions, and discontinuities that are not captured by a smooth "growth vs dissolution" picture.

Common non-equilibrium events include:

- **Learning rate warmup and sharp schedule transitions.** Even "smooth" schedules are purposeful injections of nonstationarity. Warmup is a ramp from one regime to another, and decays are deliberate regime shifts.
- **Data mixture changes.** Curriculum stages, domain upweighting, adding code late, adding instruction data late, or filtering certain content are abrupt changes in the driving medium. These can cause distributional shocks.

- **Optimizer state transients.** Adaptive optimizers accumulate moving averages. When the data distribution shifts, those averages can become temporarily miscalibrated, causing overshoot or drift.
- **Precision and system-level discontinuities.** Mixed precision, dynamic loss scaling, kernel changes, or hardware-induced numeric quirks can introduce sudden behavior changes that are not "thermodynamic."
- **Checkpoint selection and restart.** Training is sometimes paused, resumed, or branched. That is an external intervention that has no analogue in passive physical growth.
- **Post-training objective shifts.** Going from next-token prediction to preference optimization is not a small perturbation. It is a redefinition of what "good" means.

These are not edge cases. They are routine. They are the reason training is better thought of as a controlled dynamical process than as a passive relaxation toward equilibrium. The near-equilibrium frame can still guide you—especially by warning you about shocks and the need for correction forces—but it cannot be treated as a literal model of the system.

A better description is that training contains alternating regimes: exploration-like phases, consolidation phases, and intervention phases. Some of these are far from equilibrium by design. The skill of training is to sequence them without triggering defect cascades.

12.2 Representation Learning as Not Purely "Lattice-Like"

A crystal lattice has a clear unit structure: repeated identical components arranged in a regular geometry. Neural network representations are nothing like that. They are distributed, context-dependent, and polysemantic. A single neuron or attention head can participate in multiple functions. The same parameter can contribute to many behaviors, and the same behavior can be realized by many parameters.

Three mismatches matter:

- **No fixed "unit cell."** There is no single repeating local motif that composes into global structure. The model learns a hierarchy of features that change with depth, with context, and with training stage.
- **Superposition and entanglement of features.** Language models often represent multiple features in overlapping subspaces. This is unlike a lattice, where each site has a well-defined occupant.
- **Function depends on interaction, not location.** In a lattice, structure is spatial. In a network, structure is functional and relational. A "circuit" is a pattern of interactions across layers, not a physical adjacency.

Because of this, “defects” are not localized in the same way. A defect in a crystal can often be described as a specific dislocation or inclusion. A defect in an LLM—like a sycophantic tendency or a hallucination mode—can be diffuse, spanning many parameters and triggered by context.

So what part of the lattice idea survives? The part that survives is not the geometry; it is the notion of **coherence under perturbation**. A good representation is one that supports stable behavior across variations. That is closer to an error-correcting code or a robust attractor than to a rigid lattice.

If you want a metaphor closer to representation learning than crystals, you might use:

- **Energy landscape shaping.** Training carves basins and ridges in a high-dimensional landscape.
- **Error-correcting structure.** Good representations allow correct outputs to be recovered under noisy or partial cues.
- **Manifold alignment.** Training shapes a mapping from input sequences to internal states that are organized by semantics and intent.

These metaphors are less tactile than crystal growth but more faithful to how representations actually behave.

12.3 Emergence, Phase Changes, and Sudden Capability Jumps

One of the biggest failures of a smooth near-equilibrium story is that LLM capabilities often appear to change discontinuously. A model trained slightly longer or made slightly larger can suddenly begin to do something it could not do before: follow multi-step instructions, solve certain reasoning problems, or maintain longer-range coherence. These transitions look like phase changes.

There are at least three reasons such jumps can happen:

- **Threshold effects in representation quality.** Some tasks require a minimal level of internal abstraction. Below that threshold, the model cannot even approximate the behavior reliably; above it, behavior becomes accessible and improves rapidly.
- **Circuit formation.** Certain capabilities depend on specific interaction patterns across layers. These patterns may form only after other representations mature. Once the circuit exists, it can be used widely, producing an apparent jump.
- **Evaluation sensitivity.** Many benchmarks are thresholded. A small improvement in underlying competence can translate into a large jump in measured score once it crosses a cutoff.

This is not well-captured by “slow defect reduction.” It is closer to the dynamics of **self-organization**: the system accumulates partial structure until a new stable pattern becomes possible, then snaps into it.

Crystallization does have phase transitions (nucleation, facet changes), but the mapping is imperfect. In training, the “phase transition” is not a change of matter; it is a change of accessible computation. New behaviors emerge when the learned internal geometry crosses certain thresholds.

This matters because it changes how you interpret late training. Some late-phase time is indeed polishing and tail coverage. But some of it can be waiting for a threshold-crossing event: the emergence of a new circuit or abstraction. The near-equilibrium frame alone can make you think late training is only incremental. In reality, it can also be the period where discrete new capabilities appear.

So what replaces the analogy here is a concept from complex systems: **emergent order under gradual parameter change**. The system’s macroscopic behavior can change abruptly even when the microscopic updates are small.

12.4 A More General Principle: Reversible Exploration Plus Irreversible Commitment
Once you strip away the literal lattice story, what remains is a principle that explains both slow refinement and sudden jumps:

Good learning systems allocate time to reversible exploration, then consolidate what works into irreversible commitment.

This principle has two parts.

Reversible exploration means the system has room to try hypotheses without locking them in. In training, this is supported by:

- Stochasticity (minibatch noise, dropout-like perturbations)
- Moderate step sizes that don’t over-commit
- Diverse data exposure that prevents shortcuts from stabilizing
- Safety constraints that prevent exploitation of narrow reward signals

Exploration is where the system searches for representations that can support broad behavior. It also explains why early training can be relatively fast and energetic: you want movement and discovery.

Irreversible commitment means the system eventually stabilizes structure so it is reliable and reusable. In training, this is supported by:

- Learning-rate decay and late-phase polishing
- Averaging (EMA/SWA) and smoothing of the trajectory
- Regularization that discourages brittle, high-gain solutions
- Evaluation-and-selection: choosing checkpoints that demonstrate stability across tests
- Post-training constraints (like KL penalties) that prevent drift

Commitment is where you pay for reliability. It is also where you reduce variance and eliminate defect attractors.

This principle also accounts for emergence:

- During exploration, the system may gradually accumulate partial structure.
- At a threshold, a new stable pattern becomes possible; the system snaps into it.
- Commitment then consolidates and polishes that new pattern.

So the replacement is not a different metaphor; it is a design principle: build training pipelines that explicitly manage the exploration-to-commitment transition.

In that light, the "near-equilibrium" idea becomes a special case: near-equilibrium is one way to maintain reversibility during growth while still allowing net progress. But the true target is broader: **keep learning reversible enough to avoid locking in defects, then commit slowly enough to make good structure reliable.**

That is the durable lesson that survives even when the crystal analogy breaks.

13. Conclusion: Reliability Is Slow Because Self-Correction Is Slow

It is easy to confuse training time with inefficiency. If you think of learning as simply "absorbing information," then long training runs look wasteful: why can't we just push harder and finish sooner? The near-equilibrium frame offers a different interpretation. Much of what you are paying for—especially in the later phases—is not bulk capability accumulation. It is self-correction: the gradual filtering-out of brittle shortcuts, the reduction of defect-like failure modes, and the stabilization of behavior under variation. Self-correction has its own time constant. You can overwhelm it by pushing too hard, but you cannot eliminate it without accepting a defect-rich model.

Reliability is therefore slow for the same reason high-quality physical growth is slow: the system needs repeated opportunities to reject mistakes and settle into robust structure. In language models, those “mistakes” are not merely wrong tokens. They are unstable behaviors: brittle prompt dependence, spurious correlations, memorization artifacts, reward-hacked compliance, and cascading failures in tool-using loops. Reducing these is not a one-shot operation. It requires extended training in regimes where correction forces can operate, plus careful data chemistry and post-training constraints.

The bottom line is not that speed is impossible. It is that speed without stronger correction is a false economy. The run finishes earlier, but you spend the savings later in the form of regressions, safety incidents, brittleness, and costly post-hoc patching. When you see training time as the price of self-correction, the shape of modern training recipes stops looking like tradition and starts looking like necessity.

13.1 The Core Claim Restated in Operational Terms

The core claim can be stated without metaphor:

- Training time is long because reliable generalization requires many small, stable updates rather than fewer large, destabilizing updates.
- Many failure modes are suppressed only by repeated exposure to diverse data and repeated correction under low step sizes.
- The late phase is slow because it is dominated by tail phenomena and by consolidation dynamics that cannot be safely accelerated without embedding defects.

Operationally, this implies a concrete tradeoff:

- If you increase effective step size or reduce steps too aggressively, you may still reach low training loss, but you will often increase brittleness, shortcut reliance, and regressions.
- If you increase batch size to exploit more hardware, you may gain throughput but lose the stochastic “reversibility” that helps avoid sharp, defect-prone solutions, unless you introduce compensating correction forces.
- If you shift data mixtures abruptly or train longer on contaminated data, you may harden undesirable behaviors rather than polishing them away.

The near-equilibrium thesis is therefore not a claim that “slow is always better.” It is a claim about balance: progress is best when your system can correct itself nearly as fast as it commits new structure. When commitment outruns correction, defects accumulate. When correction

dominates too strongly, progress slows unnecessarily. The art is to stay in the band where both move together.

13.2 Implications for Frontier Scaling and Smaller-Model Training

The conclusions apply differently at the frontier and at smaller scales, but the principle is the same.

For frontier scaling:

- **The stability corridor narrows.** Larger models and larger runs are more sensitive to rare events, distribution shifts, and subtle numerical issues. The cost of a defect is amplified because the system is used broadly and because tool-use and agents turn minor defects into cascades.
- **More compute does not automatically buy shorter time.** Hardware scaling increases throughput, but it also pushes you into regimes (large batch, high parallelism, complex systems) where stability and communication become limiting. The wall-clock time can remain stubborn because the system's self-correction time constant has not changed.
- **Alignment pressure grows.** As models become more capable and more widely deployed, the tolerance for defect modes drops. That increases the demand for post-training correction forces (constraint-based optimization, evaluation harnesses, selection). Those forces trade raw capability for controlled behavior, which often means more training phases, more careful schedules, and more time.

For smaller-model training:

- **You can often move faster, but the reliability gap is still real.** Smaller models may be less sensitive to some instabilities and cheaper to iterate on, but they still exhibit the same defect families: shortcuts, brittleness, memorization artifacts, and reward-hacking tendencies under preference optimization.
- **Data quality can matter even more.** Smaller models have less capacity to "average out" impurities. A skewed or contaminated dataset can dominate behavior quickly. Clean mixture design can produce outsized gains in reliability relative to compute.
- **Correctness can be cheaper than robustness.** A small model can be trained to look correct on common patterns quickly, but making it robust under paraphrase, long-context, or adversarial prompts still requires deliberate correction and broader evaluation. The time constant shifts, but it does not vanish.

So the implication is not “only big models need slow training.” It is that reliability is a universal cost. Scaling makes the cost larger and the penalty for defects higher, but the underlying dynamic is the same across sizes.

13.3 A Final Synthesis: Stable Progress, Fewer Defects, Better Generalization

The paper’s synthesis is a disciplined way to connect speed, quality, and generalization:

- **Stable progress** comes from operating near the edge of stability, not beyond it—moving fast enough to learn efficiently while remaining within regimes that preserve self-correction.
- **Fewer defects** come from treating correction forces as first-class: weight decay and norm control, perturbation mechanisms that induce robustness, invariance pressure via data diversity and augmentation, smoothing via EMA/SWA, and shock absorbers like gradient clipping. Equally important is solution chemistry: balanced mixtures, controlled curricula, and data hygiene.
- **Better generalization** emerges when the model is not forced to rely on shortcuts and brittle boundaries. Generalization is not only a function of scale; it is a function of how the training process filters what it commits. A model that has had time and structure to reject unstable attachments behaves more predictably under shift, perturbation, and long-tail queries.

That returns us to the title-level message. LLM training takes so long because we are not merely building a bigger model. We are trying to build a model that works reliably across an enormous space of inputs, styles, and contexts—under conditions where mistakes can be subtle, rare, and compounding. The cost of that ambition is time spent in regimes where the system can correct itself. Reliability is slow because self-correction is slow. The most direct path to better models, therefore, is not only more compute, but better correction: cleaner data chemistry, stronger stabilizers, and training designs that respect the irreducible time constant of defect rejection.

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Speed vs Reliability
Stability
Instability
Defects
C/3
Clean Data
Quality Growth